
NCHRP Web-Only Document 90 (Project 17-23): Contractor's Final Report

Safety Impacts and Other Implications of Raised Speed Limits on High-Speed Roads

Final Report

Prepared for:
National Cooperative Highway Research Program
TRANSPORTATION RESEARCH BOARD
OF THE NATIONAL ACADEMIES

Submitted by:
Kara Kockelman
CRA International, Inc.

March 2006

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DETAILS

0 pages | | PAPERBACK
ISBN 978-0-309-43216-0 | DOI 10.17226/22048

AUTHORS

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ACKNOWLEDGMENT

This work was sponsored by the American Association of State Highway and Transportation Officials (AASHTO), in cooperation with the Federal Highway Administration, and was conducted in the National Cooperative Highway Research Program (NCHRP), which is administered by the Transportation Research Board (TRB) of the National Academies.

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Acknowledgements

The work described in this report was performed for NCHRP Project 17-23 by a team consisting of Prof. Kara Kockelman and CRA International (formerly Charles River Associates). Prof. Kockelman is an Associate Professor at the University of Texas at Austin, and her work was carried out under a subconsulting agreement between CRA International and that University.

Prof. Kockelman and Dr. Jon Bottom of CRA International were the co-Principal Investigators of the project and are the principal authors of this report. Other major contributors to the report include Young-Jun Kweon, Jianming Ma, and Xiaokun Wang, graduate students of Prof. Kockelman. In addition, Masroor Hasan and David Cuneo, Senior Associates at CRA International, contributed to the survey-related portions of the report.

Abstract

This report describes the analyses performed and results obtained by a study of safety and other impacts of speed limit changes on high-speed roads.

Safety-related analyses were based on a comprehensive framework of the disaggregate relationships between speed limits, driver speed choices, crash occurrence and crash severity. Using a variety of datasets, the project conducted numerous statistical analyses to elucidate and quantify these relationships. It was found that a speed limit increase on a high-speed road is generally associated with a less-than-equivalent increase in average vehicle speed: a 10 mi/h speed limit increase, for example, corresponds to average speeds around 3 mi/h higher. The project identified a relatively small but statistically significant correspondence between speed limits and total crash rates: a speed limit increase from 55 to 65 mi/h on an "average" high-speed road section would be associated with a crash rate increase of around 3%. Finally, the project found a statistically significant association between speed limits and the distribution of injury severities following a crash. For example, the project's models predict that a speed limit increase from 55 to 65 mi/h on the average section would be associated with a 24% increase in the probability of an occupant being fatally injured, once a crash has occurred. Considering that the crash rate itself increases slightly with a speed limit increase, overall fatality rates are predicted to rise by slightly higher percentages. However, the association between speed limit and injury severity dominates the overall fatality rate result.

The magnitude of some of these relations between speed limit changes and safety factors is subject to uncertainty because of data limitations. In particular, most of the available datasets had data on roads with different speed limits, rather than before-after data on roads that experienced speed limit changes. However, observing injury rate changes on a single road after a speed limit increase is not the same as observing injury rate differences across two existing roadways with different speed limits. Average speed differences are estimated to be higher in the latter, on the order of 6 mi/h (rather than 3 mi/h) for every 10 mi/h difference in speed limit. This data distinction is expected to translate into over-estimates of the estimated magnitude of the injury severity distribution changes following a speed limit change. Nonetheless, even after making allowances for such effects, the relationship between typical speed limit changes on high-speed roads and the injury severity distribution would in many cases remain statistically and practically significant.

The investigation of non-safety impacts relied on published literature, unpublished reports by state DOTs of speed limit change impacts, and results of surveys of state DOT and police officials. The study considered economic, environmental and other non-safety impacts of speed limit changes. The higher speeds resulting from a speed limit increase lead to travel time savings that have an economic value. The vehicles most likely to experience such savings are those making long-distance trips primarily in rural areas, where vehicle speeds are not significantly constrained by congestion. On the other hand, vehicles have higher operating costs at higher speeds; for a typical passenger car trip, the operating cost increase associated with a speed limit increase of 55 to 65 mi/h is roughly half the value of the reduced travel time. Approaches for determining the economic costs of injuries and fatalities were also reviewed. Little is known regarding the air quality and noise impacts of speed limit changes; the few available studies suggest that these impacts are very small to negligible. No reliable information was found regarding possible impacts of speed limit changes on business and commerce. Similarly, available data do not allow definite conclusions to be drawn regarding the impacts of differential light/heavy vehicle speed limits.

Executive Summary

NCHRP Project 17-23 is a study of the safety and other impacts of speed limit changes on high-speed roads. The work was carried out by a team consisting of Prof. Kara Kockelman and her students, and CRA International, Inc. (formerly Charles River Associates). Prof. Kockelman is an Associate Professor at the University of Texas at Austin.

To accomplish the project objectives, the project team carried out activities in a number of areas:

- A review of relevant literature, covering a broad range of topics relevant to this study. These included prior studies of the safety impacts of speed limit changes, discussions of statistical methodology applicable to the particular issues presented by traffic safety analyses, reviews of non-safety impacts of speed limit changes, and analyses of the effects of differential speed limits between light duty and heavy duty vehicles (e.g. cars and trucks).
- An Internet-based survey of State Departments of Transportation. The survey focused on each DOT's decision-making processes about speed limit changes, but also obtained basic information about traffic volume and safety data availability, and a number of other issues.
- Telephone surveys of a number of State Highway Patrol or equivalent agencies. Here the intent was to obtain information regarding the responses of these agencies to the NMSL repeal, especially regarding changes in the deployment of traffic enforcement resources.
- Collection of data relating to the effects of speed limits on traffic safety, and the analysis of this data to identify and quantitatively model the various ways in which speed limits directly and indirectly affect safety. Analyses of speed choices (their central tendencies and variability) were undertaken for data from high-speed roadways in several regions (including Washington State, Southern California and Austin, Texas). Crash frequency was modeled as a function of roadway design and use characteristics, while relying on both discrete and continuous models of panel data from across Washington State. Crash severities were modeled using heteroscedastic ordered logit models, as applied to both Washington and U.S. datasets. These analyses were the major focus of the project effort, and were primarily carried out by Prof. Kockelman and her students.

The principal analyses and conclusions of this work are summarized below.

Safety Impacts of Speed Limit Changes

The safety-related analyses were based on a comprehensive framework of the disaggregate relationships between speed limits, driver speed choices, crash occurrence and crash severity. The analyses drew on a variety of data types including loop detector measurements, stated preference surveys and revealed choices, and crash records containing information about crash counts and severities, vehicles and their occupants, and roadways and their environments. The project made extensive use of data obtained from Washington State because of its quality and state of preparation. However, data from a national driver safety survey, vehicle speed data from Southern California and Austin, Texas, and a national sample of crash records were also used. The analyses applied state-of-the-art statistical methods to address a number of data characteristics that complicate traffic safety analyses. The project's datasets and analyses are thoroughly described in Chapter 4 of this report.

It should be noted that, following the project's original scope of work, our data, analyses and conclusions pertain to speed limit increases on high-speed roads. Most (but not all) of our data concerned high-type roadways (Interstates and freeways) with full access control. Our conclusions cannot be extended to predict the safety impacts that might be associated with speed limit increases on lower speed roadways.

Speed Choice Models

Analyses of driver speed choices were intended to illuminate the relationships between speed limits and actual driver behavior, as this is reflected in average vehicle speeds and speed variability. A number of analyses were carried out; two in particular are highlighted here.

A study of speed limit changes in Washington State (section 4.2.4) was based on a before-after comparison of four sites: two urban and two rural, as well as two that experienced speed limit changes and two that did not. The analysis showed that a 5 mi/h speed limit increase at two sites was associated with an increase in average speeds of 1.2-1.6 mi/h, and with a 5 mi^2/h^2 speed variance increase at the rural site. Over the same period, the sites that did not experience a speed limit change exhibited essentially no changes in their traffic speed characteristics, suggesting that the "spillover" effect (the impact that a speed limit change on one road may have on parallel facilities) in this case was small or negligible.

The analysis of individual vehicle speed data obtained from a small cross-section dataset of radar gun speed measurements on roadways in Austin, Texas (section 4.2.3). This was the only source of individual vehicle speed data available to the project and speed limits were not changed during the study period. The analysis identified a number of engineering, environmental and traffic characteristics that influence average speed and speed variance. Comparing different roadway sections in the cross-sectional analysis, it was found that a 5 mi/h difference in speed limits was associated with a roughly 3.2 mi/h difference in average vehicle speeds. A particular highlight of this analysis was its demonstration that the impact of speed limits on vehicle speed *variances* is, at most, very small.

It is noteworthy that the before-after analysis of vehicle speeds on roads that experience a speed limit change suggests a much more moderate response to the change than does the cross-sectional analysis of speeds on roadways with different limits (e.g., 3 mi/h change in actual speeds following a 10 mi/h change in speed limits, rather than the 6 mi/h change that a cross-sectional analysis would suggest – a factor of 2 difference). Existing literature, which is frequently based on before-after analyses, also tends to support the lower result. Most of the project's speed choice model analyses involved cross-sectional data, however, because the Washington sample of before-after data speed and crash data was felt to be too small for use in disaggregate model development. Consequently, the magnitude of the effects of speed limit changes on average speeds may be overestimated here.

Moreover, since predictions of the overall effects of a speed limit change on safety depend in part on expected driving speed changes, an overestimate of the latter will propagate through the model system and may lead to an overestimate of the overall safety effects of a speed limit change. This caveat should be kept in mind when examining predictions of overall speed limit change effects. However, even allowing for a possible overestimate of these effects, the magnitudes of the speed limit change effects remain in most cases both statistically and practically significant.

Crash Occurrence Models

The results of the project analyses of the statistical association between speed limits and total crash rates suggested only slight effects. This work is described in Section 4.3. The project's main work on crash occurrence models was based on datasets obtained by clustering Highway Safety Information System (HSIS) roadway segments over several years of data.

Two separate analyses of this dataset found that, other things equal, the statistical relationship between speed limit and total crash rate is concave, with a maximum around 70 mi/h. (This was the highest observed speed limit in the dataset, and the model was not extrapolated beyond that value.) For a "typical" high-speed roadway section, a 10 mi/h speed limit increase is associated with a 2.9% to 3.3% increase in the overall crash rate.

Injury Severity Models

Injury severity models apply when crashes have occurred, and are then used to estimate the associated distribution of injury severities.

The project used HSIS data for Washington State as well as the National Automotive Sampling System (NASS) Crashworthiness Dataset (CDS) to estimate occupant-based injury severity models (sections 4.4.1 and 4.4.2).

Both models are consistent in that they associate sizeable percentage increases in the rates of incapacitating and fatal injuries with a 10 mi/h or higher speed limit increase. However, the magnitudes of the increases calculated by the two models are quite different. For typical speed limit increases, the model developed from Washington State data on high speed roads predicts an increase in fatalities in the range of 7%-39% following a crash, while the model estimated from NASS CDS data on all roads predicts crash fatality rate increases in the range of 31%-110%, or roughly twice as high. Of the two sets of results, it is likely that the model developed from Washington State HSIS data is more applicable to the analysis of speed change impacts on *high-speed* roads because the estimation dataset contained only data on such roads. The NASS dataset offered a much wider range of roadway types and speed limits; thus, its speed-related results are more striking. (It is rare that vehicle occupants die on low-speed roadways.) For this reason, the lower range of fatality rate changes is likely to be more appropriate when crafting speed policies for high-speed roadways.

Overall Effects

Within the comprehensive framework described above, the overall safety effects associated with a speed limit change are determined by tracing its separate and inter-related effects on driver speed choice, crash rates, and the probabilities of different injury severity levels.

For example, considering that the crash rate itself increases slightly with a speed limit increase, the overall change in the fatal crash rate following a speed limit increase will be slightly higher than just the increase in the probability of a fatality when a crash occurs. Broadly speaking, however, the association between speed limit and injury severity dominates the overall relationship between speed limit and overall injury or fatality counts. The following table illustrates this point.

Safety Effects Associated with a 10 mi/h Speed Limit Increase on High Speed Roads

Increase in Speed Limit (mi/h)	Change in Average Driving Speed (mi/h)	Change in Total Crash Count	Change in Probability of Fatal Injury	Total Change in Fatal Injury Count
55 to 65	+3	+3.3%	+24%	+28%
65 to 75	+3	+0.64%	+12%	+13%

Note: Calculations assume average high-speed roadway geometry.

It can be seen from the above that in both cases a 10 mi/h speed limit increase is estimated to result in a 3 mi/h increase in average driving speed.

In the lower speed limit range (55 to 65 mi/h), data analyses suggest a 3.3% increase in the total number of crashes, and a 24% increase in the probability that a crash results in a fatal injury. Together, these increases combine to a 28% increase in the number of fatalities following the speed limit increase.

In the higher speed limit range (65 to 75 mi/h), on the other hand, the increase in the total number of crashes is considerably smaller (0.64%). This is an illustration of the concave relationship between crash rate and speed limit described above. Although the statistical analysis does not provide an explanation for the form of this relationship, it may be that drivers are naturally more cautious at higher speeds, or that the roads deemed suitable for 75 mi/h speed limits are intrinsically safer, so that the crash rate effect of increasing speed limits to this level is attenuated. For this speed limit increase, the predicted increase in the probability of a fatality in a crash is 12%, again lower than for the 55 to 65 mi/h speed limit increase. Explanations similar to those suggested above may apply here as well. The overall effect of these increases is a 13% increase in total fatalities, which is slightly less than half the fatality increase predicted for a 55 to 65 mi/h speed limit increase. The explanations for this smaller overall increase follow directly from those for the individual effects that contribute to it.

It should be noted that predictions of injury severity distribution changes following speed limit changes, such as those mentioned above, require the application of both speed choice models and injury severity models. The crash severity models were based on cross-sectional data and, as was discussed above, may overestimate the speed change impact by a factor of roughly 2 when compared to the results of actual before-after studies on individual roadways. This implies that the predictions of injury severity changes following a speed limit change may be based on travel speed differences that are themselves too high. This could, of course, result in an overestimate of the injury severity impact, perhaps by a factor of more than 2. Nonetheless, even after making allowances for such effects, the relationship between typical speed limit changes on high-speed roads and the injury severity distribution would in many cases remain statistically and practically significant.

It is interesting to note that some (but by no means all) studies have found significant increases in fatality rates on high-speed roads following the 1987 NMSL relaxation from 55 to 65 mi/h on rural interstates. Fatality rate increases in the range of 30%-57% have been reported, using aggregate data. The corresponding prediction of the HSIS-based model is 24% for a “typical” high-speed roadway. Strictly speaking, these values cannot validly be compared; nonetheless, it is striking that our result, although slightly lower, is in the same general range as the values found by these other studies. While this is not a validation of the HSIS-based model, it is fair to say that its predictions are roughly consistent with the overall NMSL relaxation fatality impacts found by some researchers, using more aggregate datasets and statistical methods less able to account for their specific characteristics. Our results, however, provide considerably more insight into the various effects of speed limit changes on speed, crash probability, and the injury severity distribution following a crash.

Secondary Effects

It is sometimes argued that changes in the speed limit on one road or road class may affect the distribution of traffic across other roads and road classes, from driver reactions either to the speed limit change itself, or to the associated enforcement activities (if any).

The data available to our study did not allow a systematic investigation of these potential secondary effects of speed limit changes. An analysis of these effects, at the disaggregate level pursued throughout our work, would require a detailed set of traffic volume, speed and crash data extending across all road types (including non-high speed roads) likely to be affected by driver reactions to a speed limit change, and such a dataset was not available to us.

Nonetheless, two comments can be made regarding secondary effects.

First, a before-after analysis conducted at four sites in Washington State suggested that the average speed effects of a speed limit change were confined to the roadways on which the changes occurred. Two of the sites were on roadways that experienced 5 mi/h speed limit changes; statistically significant changes in average speeds were observed at these sites, but not at nearby sites that did not experience speed limit changes. This suggests that, in this case at least, secondary effects on speeds (and perhaps volumes) were not significant.

Second, interviews conducted with state DOT and police officials regarding enforcement policy changes following the NMSL repeal suggest that any such changes were at most limited in extent and geographic scope. Thus, it appears to be unlikely that driver route choice behavior was affected in a systematic and large-scale way by changes in traffic safety enforcement practices following the NMSL repeal, and so that these secondary effects may have been minor.

Non-Safety Impacts of Speed Limit Changes

The investigation of non-safety impacts of speed limit changes relied on published literature, unpublished reports by state DOTs, and results of surveys of state DOT and police officials. This investigation was a lower-priority project effort than the analysis of safety impacts discussed above.

Economic Impacts

In broad terms, non-safety impacts of speed limit changes may include effects on economic, environmental and/or commercial conditions. Unfortunately, generally applicable conclusions regarding such effects are mostly lacking.

As noted above, speed limit increases translate into less-than-equivalent increases in average travel speed. The reduced travel times made possible by higher travel speeds have an economic value. However, when considering the system-wide impacts of a speed limit change, it must be remembered that in general not all travel will be fully affected by the change; for example, travel for which average speeds are significantly constrained by congestion will likely not experience the full impacts of a speed limit change..

Changes in average travel speed also affect vehicle operating costs. Of the various cost components that contribute to overall operating costs, running costs (those that directly result from vehicle operation) are most significantly impacted by speed; and of running cost components, fuel consumption costs are the largest portion. Under typical operating conditions on high-speed roads, a 10 mi/h speed limit increase would lead to an operating cost increase of roughly half the value of the travel time savings, further reducing the net economic benefit from higher speeds.

Other Impacts

With respect to the noise and air quality impacts of speed limit changes, the little evidence available suggests that these are small to negligible.

The project was unable to find any empirical or documentary evidence regarding possible commercial impacts of speed limit increases. The resulting (smaller) increases in average speeds of commercial vehicles should, in the medium to long term, result in opportunities for more efficient transportation and business operations. However, such speed changes are typically small, and the productivity of a commercial vehicle (and of the operations that it serves) depends only partly on its travel speed since it may spend significant time in loading/unloading operations or waiting for cargo. Thus, the impacts on business and commerce of speed limit changes are likely to be marginal.

Enforcement Policy Responses to the NMSL and Its Repeal

The project conducted surveys of State DOTs and Police Agencies to identify enforcement policy responses to the NMSL and its repeal.

It is sometimes claimed that the NMSL imposition and related Federal mandates led to a systematic concentration of speed limit enforcement efforts on high-speed roads, to the detriment of potentially more beneficial traffic enforcement efforts of other kinds or on other facility types. Available data from DOTs and state police agencies did not allow a rigorous investigation of this assertion. Nonetheless, anecdotal evidence collected by the project through surveys of state DOT and police officials across the country does suggest that neither of these things happened systematically or on a large scale.

Some respondents acknowledged that there was a concern in their agencies to demonstrate compliance with the NMSL in order to avoid Federal sanctions. However, respondents were adamant that no enforcement actions taken during the period of the NMSL were of a nature to compromise traffic safety. Similarly, respondents cited no examples of systematic changes in enforcement practices away from speed limit enforcement on high-speed roads following the NMSL repeal. Indeed, several respondents and DOT reports noted that speed limit enforcement activities actually became *more* intensive on high-speed roads in the period following the repeal.

The evidence suggests that the response of most police agencies to the NMSL relaxation and repeal generally took more measured forms: for example, reduced tolerance for speeds higher than the new limits together with, in some cases, a new speeding fine structure and/or an aggressive information campaign to notify the public of the tougher post-repeal policy.

Data Recommendations

The methods used in this work were guided, and limited, by the extent and quality of existing datasets. Consequently, the project has a number of recommendations regarding future data collection efforts to support fundamental research into crash causality and characteristics.

Research-oriented data collection efforts should, as much as possible, be complementary to and build on the crash, traffic, and highway inventory data collection efforts routinely carried out. Given these sources of currently available data, it is worthwhile to focus research-oriented data collection in a few specific ways.

First, traffic safety research would benefit from the collection and assembly of additional *types* of information on the characteristics of roadways and their environments. This could include information on pavement and weather conditions; the presence and nature of embankments, barriers and culverts; driveway and cross-road frequencies; clear zone width; and sight distances. None of the datasets that the project analyzed contained such data.

Second, as a practical matter it would be more efficient to concentrate near term research-oriented data collection efforts on the high-speed roadway subsystem. Over the longer term, it would be desirable to extend such data collection efforts to other components of the overall system.

Data producing agencies should be encouraged to adopt consistent geo- or linear referencing systems to facilitate the assembly of integrated sets of disparate data types. Furthermore, agencies should be encouraged to preserve collected data in the most disaggregate form feasible, rather than aggregating it in order to reduce archiving costs. A dataset containing actual vehicle speeds, year-round traffic counts, design attributes, and crash information for a thousand homogeneous sites over several years would go a long way toward making these analyses more directly connected and their results more robust.

1 Introduction

1.1 Project Background

Three major changes in national-level speed limit policy have occurred since 1974:[1]

- On January 1, 1974 President Nixon signed into law a National Maximum Speed Limit (NMSL) of 55 mi/h. The law established a maximum speed limit applicable to all states and roadways, and provided for penalties (the withholding of Federal highway funds) for states that allowed traffic speeds in excess of 55 mi/h.
- The Surface Transportation and Uniform Relocation Assistance Act, enacted on April 2, 1987, relaxed the 1974 Federal NMSL mandate by allowing states to set speed limits of up to 65 mi/h on interstate roadways passing through areas with population less than 50,000 ("rural interstates").
- The NMSL was completely repealed by the National Highway System Designation Act, which President Clinton signed into law on November 28, 1995. Section 205(d) of this law returned to states the authority to set speed limits (or, indeed, to not establish speed limits at all) on the roadways within their boundaries, effective December 8, 1995.

Most states have used the authority granted in the 1987 and the 1995 legislation to increase speed limits on some categories of roadway.

Despite numerous studies of effects of these speed limit increases, it is fair to say that their impacts on traffic safety are not yet completely understood. Traffic statistics show that aggregate crash rates have not risen in a dramatic fashion since the speed limit changes and, indeed, some scholars have suggested that highway fatalities have actually *fallen* as a result of the increased limits. In fact, the empirical research has left about as many questions unanswered as it has been able to answer, and there still remains much controversy in both the academic and the practitioner communities regarding the relationships between traffic safety and speed limits.

With this background, the National Cooperative Highway Research program issued in mid-2002 a Request for Proposals for project 17-23, *Safety Impacts and Other Implications of Raised Speed Limits on High Speed Roads*.

NCHRP project 17-23 is generally intended to provide guidance for state highway officials and transportation policymakers who are concerned with evaluating and setting highway speed limits. The study's primary objective is to extract from available data useful answers to questions like these:

- What is the relationship between speed limits, actual driver speeds, and the crash characteristics of different highways? How can highway officials use available data to make informed judgments about the likely impact of changes in speed limits on driver behavior, crash rates, and the severity of crashes on a stretch of roadway?
- What are the *systemwide* impacts when a speed limit is changed on a particular road-segment, apart from the safety implications on those segments themselves? Are there

[1] During World War II, a National Maximum Speed Limit of 35 mi/h was enacted to conserve fuel and rubber. This was repealed after the war.

significant implications for safety on other roadways? Are there impacts on the environment or the economy due to the traffic changes that result when speed limits are changed?

Although the primary emphasis of the study is on the safety impacts of speed limit increases, the project scope of work also stipulated that some attention should also be paid to their non-safety implications as well.

The study comes at a propitious time: recent years have seen the development of both *new data* sources and *methodological advances* that are applicable to the analysis of traffic safety issues. Past traffic safety analyses have not always paid adequate attention to issues of statistical methodology: for example, an appropriate definition of the "before" and "after" cases when investigating the effects of a traffic safety measure; or an appropriate recognition of the effects of data aggregation. In recent years, however, traffic safety researchers have become much more aware of these issues, and in some cases have developed methods to address or circumvent the analytical difficulties. In cases where this has not been possible, the limits of valid statistical inference are at least now clearer than they might have been in the past.

Moreover, the increasingly broad deployment of automatic traffic data collection equipment, particularly since the NMSL repeal, is producing a large set of vehicle count, detector occupancy and, in some cases, speed measurements, covering individual highways and sometimes entire highway systems. In some cases, these data are available at a level of disaggregation that reduces some of the statistical difficulties created by data grouping. Such dynamic traffic data, when combined with crash reports and descriptions of highway characteristics, provide a very detailed description of the traffic environment at or around the time of a crash, and lend themselves to detailed analyses of factors that influence crash occurrence.

1.2 Major Project Activities

To accomplish the project objectives, the project team carried out a variety of activities. These can be grouped into the following major activity areas:

- a review of relevant literature, covering a broad range of topics relevant to this study. These included prior studies of the safety impacts of speed limit changes; discussions of statistical methodology applicable to the particular issues presented by traffic safety analyses; reviews of non-safety impacts of speed limit changes; and analyses of the effects of differential speed limits between light duty and heavy duty vehicles (e.g. cars and trucks);
- an Internet-based survey of State Departments of Transportation. The survey focused on each DOT's decision-making processes about speed limit changes, but also obtained basic information about traffic volume and safety data availability, and a number of other issues;
- telephone surveys of a number of State Highway Patrol or equivalent agencies. Here the intent was to obtain information regarding the responses of these agencies to the NMSL repeal, and especially regarding possible changes in the allocation or deployment of traffic enforcement resources;
- the collection of data relating to the effects of speed limits on traffic safety, and the analysis of this data to identify and quantitatively model the various ways in which speed limits directly and indirectly affect safety. This was the major focus of the project effort, and was primarily carried out by Prof. Kockelman and her students.

1.3 Organization of the Report

Chapter 2 summarizes the documents that were included in the project's literature review. The main conclusions of prior studies of speed limit safety impacts and of methodological issues are briefly presented and commented on, both because of their intrinsic interest and also as motivation for the analysis approach and methodology choices that were adopted for this project. Conclusions from the review of studies of non-safety impacts of speed limit changes, and of differential light- and heavy-duty vehicle speed limits are also presented.

Chapter 3 describes the organization, conduct and results of the Internet survey of State DOTs, and of the subsequent telephone survey of State Highway Patrols and similar agencies.

Chapter 4 presents in detail the data collection and analysis work carried out during the project. It discusses the project's data sources and the analyses performed and statistical models estimated with each.

Chapter 5 summarizes the project's main findings, conclusions and recommendations.

A number of appendices provide additional detail about particular activities and analyses that the project carried out.

2 Literature Survey

2.1 Overview

This chapter reviews the published literature on the impacts of speed limit changes. It first considers the studies conducted to investigate the impacts of major speed limit policy changes, focusing particularly on the three national-level NMSL policy changes in 1974, 1987 and 1995. Each of these policy changes was, in a sense, a natural experiment that generated subsequent research activity attempting to identify and quantify its impacts on traffic safety and driver behavior and, sometimes, in other domains as well. The review also examines some studies of speed limit policy changes in other countries and at the state and local level. Note that this review does not constitute an endorsement of the results of these studies. Indeed, many of the studies did not adequately address the methodological difficulties of traffic safety research. Some of these deficiencies are pointed out in the discussion; however, the intent of the review is to present an overview of prior traffic safety research, not to present an exhaustive critique of each individual effort.

The review next examines the research literature in a number of more focused areas relevant to the study activities, including the effect of speed limits on driver speed choice behavior, and the general relationships between speed and crashes. It considers various other (non-speed limit) policies that have been proposed to improve traffic safety, and summarizes research investigations of their impacts. A brief summary of prior studies of the effects of roadway design on travel speeds is also provided.

Methodological issues are next reviewed. As will be seen, analysis of the impacts of speed limit changes poses a number of quite difficult challenges, deriving both from the complexity of the various individual- and system-level responses to the changes, as well as from the limitations of typically available data. Any study of speed limit change impacts must be informed by a thorough appreciation of these methodological issues. Indeed, the conclusions of many prior studies can be called into question because of inadequacies in the analysis approaches that they followed; conversely, methodological advances have frequently been the driver of improvements in our overall understanding of speed limit change impacts. Not surprisingly, many of the documents examined in the other (non-methodological) sections of the literature review also have interesting methodological aspects, and these are highlighted as appropriate.

Finally, the literature review examines available information on the non-safety impacts of speed limit changes, and on the specific question of differential speed limits for heavy- and light-duty vehicles (e.g. cars and trucks). Regarding the former topic, the literature is dispersed among a variety of study areas, and, at the present time, a comprehensive set of conclusions is not available. The discussion uses the framework of economic cost-benefit analysis to organize and present current knowledge. The topic of differential speed limits has been more intensively investigated, and the review summarizes what is currently known.

2.2 Safety Impacts of Changes in Speed Limit Policy

2.2.1 Imposition of the NMSL in 1974

Although energy conservation was the primary reason for the 1974 enactment of the NMSL, many commentators quickly speculated about its potential impacts on traffic safety as well. There followed a number of studies examining the traffic safety efficacy of the lowered speed limit both at the level of individual states and of the nation overall.

Most of these studies employed one of two general methodological approaches:

- before-after (or pre-post) comparison (including comparisons between control and test groups and analysis-of-variance [ANOVA] comparisons); and
- cross-sectional or time-series regression analysis.

Burritt (1976) used before-after comparisons to study changes in crash counts and rates following the imposition of the NMSL. He found decreases in crash rates by all severity levels (fatal, injury, and PDO), which he attributed to reduced speeds and speed variations. Dart (1977) also conducted before-after comparisons using speed and crash count data from North Carolina, Mississippi, and Louisiana. One-way and two-way ANOVA investigations of fatalities were carried out by Labrum (1976) in Utah; and before-after comparisons of crash counts by different severity level were performed for New York and New Jersey by Weckesser et al. (1977). Tofany (1981) made state-by-state comparisons of speeds, fatalities and fatality rates between 1973 and 1977. Deen and Godwin (1985) carried out a meta-analysis, using and combining results from earlier studies.

All these studies except Labrum's concluded that the lowered speed limit brought traffic safety benefits in the particular study areas that they considered. Labrum (1976), on the other hand, concluded that the available data did not allow him to disentangle the effects of speed limit changes from those of contemporaneous changes in other factors also affecting traffic safety. In an interesting regression-based study, Forester et al. (1984) used time-series regressions and cost-benefit analysis to examine the impacts of adopting the 55 mi/h NMSL. Using yearly crash statistics for the entire U.S. from 1952 to 1979 and a sequential series of equations (for speed, speed concentration [the percentage of vehicles traveling between 45 and 65 mi/h] and fatal crashes), the researchers estimated that yearly traffic deaths fell by 7,466 as a result of the speed limit change. Moreover, they concluded that most of the saved lives resulted from reduced speed variation (which was represented by a proxy variable derived from yearly data for the entire U.S.) Their cost-benefit analysis also recognized the time losses due to lower speeds and, based on their valuation of those losses, they concluded that continuation of the 55 mi/h limit was *not* economically desirable.

2.2.2 Relaxation of the NMSL in 1987

The 1987 relaxation of the NMSL, which allowed states to set speed limits up to 65 mi/h on their rural interstate roadways, attracted considerable research interest. Methodologies applied in studies of this change ranged from naïve before-after analyses to ARIMA intervention analysis and panel data regression.

One of the advantages of before-after analyses is that they lend themselves to seemingly straightforward interpretation. Using this method, Hoskin (1986) concluded that fatalities increased on rural interstates following the 1987 change. Using 1982-1987 data for 38 states and a modified before-after analysis with odd ratios calculated, Baum et al. (1989) identified an increase of 15% in the number of crash deaths in states that increased speed limits. In a subsequent study, with 48 states, Baum et al. (1991) estimated that the number of crash-related deaths increased by 29% and the crash rate by 19% in states that set rural interstate limits at 65 mi/h; this is in contrast to 12% fewer deaths in states that retained the 55 mi/h limit.Gallaher et al. (1989) estimated the fatal crash rate for the "after" period using a linear trend regression based on 1982-1988 crash data for New Mexico's rural interstates. They compared their estimated rates under the 65 mi/h speed limit to the rates before the change, and concluded that the raised limits led to increased crash death rates. Chang and Paniati (1990) adopted a somewhat similar approach, but used ARIMA time series models to predict post-policy fatalities. They used monthly crash death counts from 1975 to 1988 for 32 states that had raised their limits. Due to a lack of "after" period data, they could not reach a conclusion as to the impact of the 65 mi/h limit. It should also be noted that their models did not incorporate exposure data (in the form of vehicle-miles of travel [VMT] or other measure of travel intensity).

Based on a naïve before-after comparison applying an ANOVA test, Lynn and Jernigan (1992) noted increases in fatal crashes, fatalities, and average and 85th percentile speeds on rural interstates in Virginia. On the other hand, they found no meaningful increases in the same measures on urban interstates. However, their analysis did not control for VMT, volumes, or other factors. Using a before-after comparison based on VMT data, Upchurch (1989) found increases in total, injury and fatal crash rates, as well as a 3 mi/h increase in average speed on rural interstates in Arizona. He also noted a slight decline in the state's overall crash rate, which may simply be a trend resulting from improvements in road design, vehicle design, and/or driver education and abilities.

Pant et al. (1992) utilized before-after methods to compare Poisson-model-calibrated average monthly crash rates on Ohio's rural interstates with 65 mi/h and 55 mi/h speed limits, and non-interstates with 55 mi/h speed limits. No change in monthly crash rates was found following the 1987 change in rural limits. Ossiander and Cummings' (2000) before-after approach employed Poisson and negative binomial regressions for estimation of "after" period crash rates for Washington. Using a 20-year panel of data (1974-1994) covering all Washington highways, they found a large increase in fatal crash rates on rural highways, while urban highway crash rates (both fatal and in total) stayed relatively constant. Increases of 5.5 and 6.4 mi/h in average and 85th percentile speeds, respectively, were also noted. However, these changes did not appear immediately following the rural-interstate speed limit increase, but instead developed gradually over the years. This trend is probably apparent across the U.S., due not only to roadway design enhancements but also to changes in vehicle design and driver experience and preferences. Congestion may tend to counteract this trend in some areas.

A number of studies of the 1987 NMSL relaxation applied cross-sectional regression techniques. Garber and Graham (1990) developed linear regression models recognizing a linear time trend and specifying monthly indicator variables for each of 40 states that raised their rural interstate speed limits to 65 mi/h. Using monthly data for rural highways between 1976 and 1988, they estimated the median effect of the 65 mi/h limit to be a 15% increase in fatality counts on rural interstates and a 5% increase on rural non-interstates. However, the results were found to vary between states, with some states experiencing a reduction in fatalities after raising the limit, and others experiencing no effect. It should be noted that this study used only two years of post-increase data, and that VMT was not controlled for. Nonetheless, the work clearly suggests that a single speed limit policy may not apply to all states or all high-speed roads. Local design factors and driver expectations are likely to play a key role in shaping appropriate policy.

Using a similar state-by-state method but considering all roads and using more recent data and VMT estimates, Lave and Elias (1994, 1997) estimated that total state fatal crash rates fell by 3.4% to 5.1% following the 1987 speed limit increase. Their 1997 study suggested that the decrease in fatalities following the relaxation of the NMSL might have resulted in part from a shift in the allocation of police resources away from speed-limit enforcement to other activities with higher marginal safety benefits, along with a shift in driver route choice away from lower-quality roads to better-engineered and safer interstates.

Time series models also have been a frequently applied methodology in safety policy analysis. McKnight and Klein (1990) used ARIMA intervention regression for fatal and injury crash data from 1982 through 1988. Based on a comparison of data for the 38 states that raised their speed limits and others that did not, they noted a 22% increase in fatal crashes on 65 mi/h rural interstates. Wagenaar et al. (1990) utilized ARIMA analysis with multiple interventions (including mandatory safety belt laws) to examine crash rates on all roads and, more specifically, on rural interstates in Michigan between 1978 and 1988. After controlling for factors including VMT, the proportion of young drivers, beer consumption and the state's unemployment rate, they reported a 19% increase in fatalities, a 40% increase in serious injuries and a 25% increase in moderate injuries on 65 mi/h rural highways. Spillover speeding was also noted, and likely contributed to the 40% increase in fatalities noted along 55 mi/h rural highways.

Rock (1995) studied the Illinois experience with the 1987 NMSL relaxation using monthly rural highway data from 1982-1991. Using ARIMA intervention regression analysis, with naïve before-after comparisons as a supplement, he found 33% increases in crashes, 40% increases in fatalities and 19% increases in injuries on the state's 65 mi/h rural highways. Moreover, he found 6%, 25% and 6% increases for each of the three measures, respectively, on 55 mi/h rural highways, supporting a spillover hypothesis. Ledolter and Chan's (1996) similar work with quarterly Iowa data from 1983 to 1991 led to an estimate of a 57% increase in fatal crashes on rural interstate highways following the speed limit increase.

Panel data analysis is a more recent method for analyzing speed limit policy. Houston (1999) applied a linear fixed-effects model (with state-specific effects) to data across a variety of road types and all 50 states between 1981 and 1995. His estimates indicate an increase in rural interstate fatalities, but reductions in fatalities on rural non-interstates, all other roads and the road system overall. This result lends support to some of Lave and Elias's (1994, 1997) conclusions, which noted a decrease in statewide fatality rates following the 1987 speed limit increases.

Greenstone (2002) used linear panel models with fixed effects (for road type and year) to track yearly fatality rates in all 50 states from 1982 to 1990. He concluded that fatality rates rose by 30% on rural interstates and fell by 17% on urban non-interstates. He also looked for – but found no evidence of – police resource reallocation after the speed limit increase.

As seen from the above, many studies found negative safety effects of the 1987 relaxation of the NMSL to 65 mi/h, while a few others (e.g., Chang and Paniati, 1990) were unable to draw definite conclusions regarding the effects. However, the studies (e.g., Sidhu, 1990; Lave and Elias, 1994, 1997) that suggested that the raised limits had no harmful impacts, and may even have had beneficial impacts, cannot be dismissed since they have a defensible basis for their arguments.

Note that the studies reviewed here all used highly aggregate data that left them unable to account for the effects of detailed roadway characteristics; and did not incorporate speed data even at an aggregate level.

2.2.3 Repeal of the NMSL in 1995

The NMSL was abolished in the 1995 National Highway System Designation Act, which returned to states the authority to establish speed limits on their roads, or indeed to not enact speed limits at all. This quickly led to a series increases in speed limits and observed speeds in a majority of states[2] – and to new studies of the safety impacts of speed limit policy changes.

Farmer et al. (1999) predicted fatality counts and rates on all highways in 31 states (24 with higher speed limits and 7 without), based on time-series regression models using data from 1990 through 1997. In contrast to the findings of Moore (1999), their calibrated models predicted a 15% increase in fatalities and a 17% increase in fatality rates on interstates in the 24 states that raised their limits; they found no statistically significant changes in the crash characteristics of non-interstate roads in those states.

Patterson et al. (2002) calibrated cross-sectional regression models of fatality rates. Their models were specified using an indicator for the change in speed limits, and estimated using 1992-1999 data for 34 states (12 states which retained their pre-repeal speed limits, 12 which raised them to 70 mi/h and 10 which raised them to 75 mi/h). They found 35 to 38% increases in fatality rates, which they attributed to the increased speed limits.

Haselton et al. (2002) applied and compared three alternative methodologies to study the impacts of speed limit changes in California: (i) Hauer's observational before-after approach; (ii) a before-after analysis with ANOVA tests; and (iii) a cross-sectional regression analysis. They analyzed freeways in California considering total, fatal and severe-crash counts, and distinguishing dark and wet conditions. They found that the simple cross-sectional regression method produced unreliable estimates. The other two approaches found increases in total and fatal crashes and crash rates following speed limit increases on the freeways studied.

Najjar et al. (2002) used a three-step sequential approach, combining before-after comparisons using t-tests for monthly crash rates and time-series trend plots for yearly crash rates. Using crash data on highways in Kansas for the period 1993 to 1998 (excluding 1996), they found no statistically significant changes in crash, fatal crash, and fatality rates on rural and urban interstates. However, significant increases were noted on two-lane rural highways for the after period 1997-1998.

In the period following the NMSL repeal, a number of state Departments of Transportation (DOT) undertook studies to plan for and assess the impacts of implementation of new speed limits. These studies were sometimes done internally, and sometimes with the assistance of local universities or research institutions. In some cases, states implemented the new speed limits on a limited set of highway sections, studied the impacts of the new limits on those sections, and

[2] 33 states raised their speed limits.

made subsequent speed limit decisions based on the results obtained. It is fair to say that, for a variety of reasons[3], almost all of these safety impact studies relied on relatively simple before-after comparisons of crash counts or rates, and contribute only marginally to a more statistically rigorous and sophisticated analysis of speed limit change safety impacts. On the other hand, some of the studies also considered non-safety impacts, and had very interesting insights on these issues. Chapter 3 reviews a number of post-NMSL state reports in greater detail.

It is notable that relatively few rigorous studies have been conducted to date on the impacts of the post-NMSL repeal speed limit changes, despite the general availability of better datasets than typically existed in the past. Data improvements include more widespread and detailed measurements from traffic detectors, and more comprehensive compilations of panel data. It is also notable that the studies investigating the 1995 NMSL repeal have tended not to make use of this panel data or of the statistical methods that have been developed to analyze them.

2.2.4 Other Investigations of Speed Limit Change Safety Impacts

The preceding sections have focused on reviews of studies of the three major changes in nationwide speed limit policy in the U.S. These studies represent a large part of the total body of published studies of speed limit policy change impacts. However, there are also studies that assess the safety impacts of speed limit changes at a local level or in other countries. Some of these are briefly reviewed here.

As an example of a local-level study, Ullman and Dudek (1987) conducted before-after comparisons of crash rates covering two years to investigate the effects of lowering limits from 55 mi/h to 45 mi/h at six urban-fringe sites in Texas. The study controlled for traffic volumes, but discovered no statistically significant changes in the average and 85th percentile speeds, or in total, injury or fatal crash rates.

Speed limit impact studies have also been conducted in other countries. Using naïve before-after comparisons, Egsmose and Egsmose (1985) used yearly fatality counts to examine the experience in Denmark with three speed limit policy changes over the period from 1970 to 1982: the initial introduction of speed limits, increased limits, and reduced limits on superhighways and rural main roads. Their study observed that lower speed limits generally corresponded to lower numbers of annual fatalities. However, because they failed to control for changes in exposure measures, it is not possible to draw strong conclusions from their results.

Johansson (1996) used time series count data regression models (Poisson and negative binomial) to analyze the effects of lower speed limits on Swedish motorways. He found a reduction in non-severe injury crashes and property-damage-only crashes, but no change in severe and fatal crashes, following speed limit reductions.

Wilmot and Khanal (1999) conducted a meta-analysis of prior studies that researched speed limit impacts from several points of view (e.g., impacts on speeds, speed dispersion, and safety). Drawing from studies in European countries (e.g., Sweden and Finland) and the U.S., they concluded that drivers choose their speeds based on their own perception of safety, implying that

[3] Including limited observation time frame, limited quality of available data, limited study resources, time pressure to make decisions, etc.

speed limits do not have a significant effect on their driving speeds. They also found that speed is not statistically associated with crash occurrence, but that it is associated with crash severity.

2.3 Effects of Speed Limit Changes on Speed Conditions

The relationship between speed limits and traffic speed characteristics is of interest because of its relevance to the connections that have been hypothesized between traffic speed and safety.

Of course, the posted speed limit is not the only determinant of driving speed. At a disaggregate level, the choice of speed is influenced by factors that comprise driver and trip-related characteristics, roadway geometry, pavement conditions, vehicle performance characteristics and the driving environment, including the speed limit.

In some particular situations, a single factor may strongly affect the driving speed. This is the case, for example, with low radius horizontal curves, and driver speed choice on horizontal curves has been particularly studied for this reason.[4] On tangent and other sections with less constrained roadway geometry, individual driver speed choices and aggregate speed characteristics generally result from the interplay of the various factors mentioned above, with speed limits frequently being an important determinant.

A number of studies that investigated the safety effects of speed limit changes also examined the effects of these changes on traffic flow speed characteristics, such as average speed and speed variance or other indicators of the distribution.

It has been found that a change in speed limit generally results in a less-than-equivalent change in average speed. For example, Burritt (1976), Dart (1977) and Forester et al. (1984) all found that average speeds fell by less than the speed limit decreases resulting from the NMSL imposition. With respect to speed limit increases, Ossiander and Cummings (2002), Jernigan and Lynn (1991), Freedman and Esterlitz (1990), Brown et al. (1990), and Upchurch (1989) found increases in average speeds by 2 to 7 mi/h following the 1987 NMSL relaxation to 65 mi/h on rural interstate highways. The project investigated this issue (section 4.2).

However, there is little consensus regarding the effects of speed limits on traffic speed variability. Burritt (1976), Forester et al. (1984), and Rama (1999) found reductions in speed variation following lowered speed limits, while Garber and Gadiraju (1992) found speed variance reductions when speed limits were differentially raised. Mace and Heckard (1991) found increases in speed variance following raised speed limits, while Ossiander and Cummings (2002), Pfefer et al. (1991), and Brown et al. (1990) found no such changes. Again, the project data analyses investigated and shed light on this issue (section 4.2).

2.4 Effects of Speed Conditions on Safety

The laws of physics (kinetic energy = 0.5 × mass × velocity^2) suggest that speed is one of the most critical factors affecting crash severity (TRB, 1998). This is one basis of the "Speed Kills" theory, which holds that increases in speed, such as those following a speed limit increase, will

[4] See, e.g., Emmerson, (1969, 1970); McLean (1981); Glennon et al. (1985); Lamm and Choueiri (1986); Kanellaidis et al. (1990); Islam and Seneyiratne (1994); Ottesen (1993); Krammes et al. (1993); Voigt and Krammes (1995); Andjus and Maletin (1998); and Abdelwahab et al. (1999).

automatically lead to higher numbers of traffic fatalities and serious injuries. Higher speed also reduces the time available for a driver to react to a dangerous situation, tends to reduce vehicle lateral stability, and may affect tire grip on the pavement.

In some contrast, however, Lave (1985) argued for a "Variance Kills" theory, as first proposed by Solomon (1964) and replicated by Cerillo (1968). The rural road data analyzed by these researchers appear to indicate that crash likelihood increases with an individual's deviation from the average roadway speed. The conclusions of this work were supported by later studies, including those of West and Dunn (1971) and Fildes and Lee (1993). Lave's argument, in turn, has been supported by work by Rodriguez (1990) and Reed (2001)

Several researchers (Fowles and Loeb 1989; Levy and Asch 1989; and Snyder 1989) have attempted to refute Lave's argument by enhancing his data and model specification. Interestingly, as Lave (1989) notes in his reply/rebuttal, their findings provide evidence for both the "variance kills" and also the "speed kills" theories. Garber and Ehrhart (2000), Forester et al. (1984), and Zlatoper (1991) also concluded that variance, as well as average speed, contribute to crash frequency.

However, none of these studies may correctly reflect the true relationships between traffic safety and driving speed characteristics, because they rely on speed data that has been spatially and temporally aggregated, and thus may be subject to the ecological fallacy, discussed below.

2.5 Safety Effects of Other Policies

Clearly, policies and measures other than speed limit regulations can also affect traffic safety, and various studies have examined these as well. Interest here is not necessarily on the particular conclusions that these studies reached, but rather on the methodological approaches that they employed, because some of these methodologies may also be applicable to speed limit research.

Among the variety of traffic safety policies, the impacts of three specific types of regulation have been studied with some attention: vehicle inspection policies, alcohol-related policies, and seat belt use policies. Results of these studies are summarized below, with a focus on the study methodology applied to each kind.

2.5.1 Vehicle Inspection Policies

Vehicle inspection regulations were originally introduced with the idea that regular verification of vehicle conditions would enhance traffic safety. Loeb (1985) used state-based cross-sectional regression models to evaluate the efficacy of vehicle inspection programs in terms of fatalities (per capita and total), and found such inspection programs to be effective.

Utilizing log-linear time series models for U.S. data from 1952 to 1982, Garbacz and Kelly (1987) found no effects of the inspection regulation on fatalities, but did note a beneficial effect of the 55 mi/h NMSL on fatality rates. Using 1947-1985 data and a similar model, but with additional explanatory variables and supplemented by cross-sectional models (with log-linear and linear specifications), Garbacz (1990) confirmed the earlier 1987 finding of no evidence for the traffic safety efficacy of the vehicle inspection programs in states having such programs.

Merrell et al. (1999) employed fixed-effects models using data from all 50 U.S. states for the period 1981 to 1993. They found no evidence of an effect of vehicle inspection requirements on fatality or injury rates. However, their data did suggest a positive effect of speed limits on fatalities (i.e., higher speed limits resulted in more traffic deaths per VMT), and no effect of seat belt laws on fatality or injury rates. Omitting the fixed effects produced contrary conclusions, thus underscoring the importance of using panel data analysis.

2.5.2 Alcohol-Related Policies

Regulations related to drinking ages and the blood alcohol concentration (BAC) of drivers are important to traffic safety. Haque and Cameron (1989) employed ARIMA intervention regression and before-after comparisons to assess the impact of the introduction of the zero BAC law in Victoria, Australia. They found that the zero BAC regulation had no effect in reducing traffic crashes, and conjectured that a lack of enforcement may explain this negative result.

Foss et al. (2001) applied structural time series regression analysis to crashes in North Carolina. They included an intervention effect for regulations lowering the legal BAC limit starting in 1993. With an already existing downward trend in alcohol-related crashes during the 1991-1996 period, their results revealed no statistically significant added effect due to the lower BAC limit.

Voas et al. (2003) evaluated the effectiveness of two alcohol-related regulations: raising the minimum legal drinking age and introducing a zero tolerance BAC limit for drivers 21 years or younger. They used a linear panel regression (with each state as a basic unit) and the logarithm of the odd ratios of alcohol-involved drivers to other drivers as the dependent variable. The two regulations were found effective in lowering the percentage of alcohol-related fatal crashes.

2.5.3 Seat Belt Use Policies

Seat belt regulation is another important policy area that may have a potentially considerable influence on traffic safety. Loeb (1993, 1995) developed cross-sectional linear regression models to examine the effectiveness on traffic safety of seat belt laws in California (Loeb, 1993) and Texas (Loeb, 1995). The California study also examined effects of raising the speed limit to 65 mi/h and found adverse effects on fatalities and injuries. Ulmer et al. (1995) compared observational data collected before and after seat belt laws changed from secondary to primary enforcement in California. They found that the observed proportions of drivers wearing seat belts increased after the change, and concluded that the enforcement shift was effective in raising the rate of seat belt use.

Loeb (2001) used similar regression models to estimate the effect of Maryland's secondary seat belt law on various driver injury rates after controlling for monthly indicators, unemployment, a time trend, and other factors; he used logarithmic injury rate as the dependent variable. He found that the effect of the law varies depending on the injury severity level, and concluded that introduction of the law reduces the rate of severe and moderate injuries but raises the rate of fatal and severe injuries.

Dee (1998) used a two-way fixed-effects linear model, including a dummy variable to indicate the existence of seat belt laws, to estimate the effects of mandatory seat belt laws on observed seat belt use. He also estimated a two-way fixed-effects binary probit model with the indicator variable and individual attributes to estimate the effects of mandatory seat belt laws on self-reported seat belt use. He showed how standard before-after comparisons overstate the effects of seat belt laws on seat belt use by about 60 percent due to a failure to account for a positive yearly linear trend in seat belt use.

Wong and Wu (1998) adopted time-series regression to assess three different safety policies in Singapore: seat belt regulation, use of breathalysers (a device that measures BAC), and introduction of the circuit training and testing system (a system to prepare new drivers for actual roadway driving). They found the seat belt law to be ineffective, but the other two policies to be effective in reducing fatalities.

2.5.4 Other Safety Measures

A number of studies have examined the efficacy of yet other safety measures. Holland and Conner (1996) evaluated the effects of police intervention on speeding on urban road segments with 40 mi/h speed limits in the U.K. Using ANOVA and Tukey B range tests, they found that warning signs (without police presence) have speed reducing effects, and that warning signs with police presence have effects lasting up to 8 weeks after the removal of these "interventions."

Pau and Angius (2001) used before-after comparisons and ANOVA tests to compare speeds with and without speed bumps to assess the effectiveness of the speed bumps in reducing speeds. Newstead et al. (2001) used a Poisson regression with monthly crash data to assess a traffic policing program in Queensland, Australia. Combined with quasi-experimental design (i.e., control group comparison in an observational study), the Poisson regressions provided evidence that the new policing program was effective in reducing total crash counts and crashes of all severity levels. However, this study did not account for any crash exposure measures.

Noland (2003) examined the traffic safety effects of roadway infrastructure improvements (e.g., additions to total lane miles, lane widths, and the number of lanes). Using fixed-effects negative binomial regressions with panel data for 50 states over 14 years, Noland concluded that engineering design improvements have not been effective in reducing fatalities and injuries, and that a large portion of the observed decline in roadway fatalities is attributable to demographic changes, increased seatbelt use, reduced alcohol consumption, and improved medical technology, rather than to roadway improvements.

Olmstead (2001) conducted a careful analysis of the effect of the Phoenix, Arizona freeway management system on the incidence and nature of reported vehicle crashes. (A freeway management system [FMS] is a system of integrated technologies intended to improve the efficiency and safety of highway travel.) Using a fixed effects negative binomial regression model, the analysis found that the FMS significantly reduced the frequency of PDO, possible injury and minor injury crashes. It found no effect on the frequency of major injury or fatal crashes. The results were robust to a variety of model specifications, including different functional forms, covariates and data.

2.6 Effects of Roadway Design on Speed

As a guide in specifying speed choice models, the project reviewed a number of prior studies that investigated the effects of roadway design and related factors on travel speed.

According to the American Association of State Highway and Transportation Officials (AASHTO, 2001), four general conditions affect driving speeds on roadways: physical characteristics of the road and roadside interference, weather, other vehicles, and the speed limit. Among these conditions, roadway design is a major governing factor of driving speeds.

Horizontal curves have frequently been chosen for study because they can be the most speed-constraining sections on roadways. However, when focus moves to vehicle speeds on general roadway segments, geometric factors do not carry the same importance as they do in curve sections. On tangent segments, no single dominating factor has been identified since many different factors besides road geometry influence the choice of driving speeds.

Table 2-1 provides a concise summary of prior studies of these issues in terms of variables employed, data size, locations and roadway types investigated.

Table 2-1 – Studies of the Effects of Roadway Design on Speed

Author	*Dep. Var.*	*Ind. Vars.*	*Sample Size*	*Location*	*Roads*	*Year*
Emmerson	V	R	-	-	-	1970
McLean	V_{it}	R, V_F	120 sites	Australia	2-lane rural hwys	1981
Glennon et al.	V_{it}	R	56 curves	FL, OH, IL, TX	-	1985
Lamm & Choueiri	V_{it}	*DC, LW, SW, AADT, (CCR)*	261 sites	NY State	2-lane rural hwys	1986
Kanellaidis et al.	V_{it}	R,	58 sites	Greece	2-lane rural roads	1990
Islam & Seneviratne	V_{it}	*DC*	8 curves	UT	2-lane rural hwys	1994
Ottesen	V_{it}	R	138 sites	NY, PA, OR, TX, WA	2-lane rural hwys	1993
Krammes et al.	V_{it}	*R, CL, DF*				
Voigt & Krammes	V_{it}	*R, CL, DF, e*				1995
Polus et al.	V_{it}	*GM*	162 sites	MN, NY, PN, OR, WA, TX	2-lane rural hwys	1997
Al-Masaeid et al.	V_{it}	*DC, SL, RI*	22 sites	Jordan	7 2-lane rural hwys	1998
Andjus & Maletin	V_{it}, V_{50}	R	9 sites	Yugoslavia	2-lane rural hwys	1998
Abdelwahab et al.	ΔV_{85}	*DC, DF*	-	Jordan	5 2-lane rural hwys	1999
Schurr et al.	V_{it}, V_{95}, $\overline{V}$	*CL, SL, AG, ADT, DF*	40 sites	NE	2-lane rural hwys	2000
Fitzpatrick et al.	V_{15}, V_{50}, V_{85}, V_{90}, V_{95}	*SL, AD*	78 sites	AK, MA, MO, OR, TN, TX	Urban/suburban streets	2002

Table Notes: $\overline{V}$ = average speed, V_{50} and V_{85} = 50th and 85th percentile speeds, respectively, *AADT* = annual average daily traffic, *ADT* = average daily traffic, *AD* = access density per mile, *AG* = approach grade, *CCR* = curvature change rate, *CL* = curve length, *DC* = degree of curvature, *DF* = deflection angle, *e* = superelevation, *GM* = geometric measure consisting of previous and following radii and tangent length , *LW* = lane width, *R* = curve radius, *RI* = rainfall intensity, *SL* = posted speed limit, *SW* = shoulder width, and V_F= desired speed of 85th percentile car. The year shown is either the year of completion of data collection or, if unavailable, the year of publication of the study.

2.7 Statistical Methodologies for Safety Evaluation

As is clear from the above review, traffic safety analysis can be complex. There are a number of difficult methodological issues that must be recognized and addressed in order to draw valid conclusions, and advanced statistical techniques are sometime needed to circumvent these issues and process available data.

This section discusses key methodological issues that complicate traffic safety data analysis, and presents an overview of the statistical techniques that are applied in traffic safety studies.

2.7.1 Methodological Issues

The following paragraphs present some of the methodological issues that complicate the analysis of traffic safety data. These issues are some of the reasons why it has often been so difficult to develop clear and unambiguous conclusions regarding the impacts of speed limit changes and other safety treatments and policies.

2.7.1.1 Crashes Are Rare Events

Crashes are, fortunately, rare occurrences. Data covering a long period of time or a large number of roadway segments must be compiled in order to obtain a sufficient number of observations to allow statistically significant conclusions to be drawn. However, a large and diverse dataset of this type will almost inevitably include considerable variation in other factors, either observed or unobserved, that may affect the phenomena (e.g. traffic safety impacts) that one wishes to analyze. This is related to the problem of confounding factors, discussed below.

2.7.1.2 Incomplete Recording of Crashes

Reporting and official recording of crashes is less than perfect. Nearly all crashes involving fatalities are probably recorded, but the probability that a crash is not recorded increases as the crash severity decreases. This phenomenon biases the data used for safety analysis, making it appear that less severe crashes occur less frequently than they actually do in reality.

For example, in a cross-country comparison Elvik and Mysen (1999) estimated global crash recording rates of 95% for fatalities, 70% for serious injuries (admitted to a hospital), 25% for slight injuries (treated as a hospital outpatient), 10% for very slight injuries (treated outside a hospital), and 25% for PDO crashes. Hauer and Hakkert (1988) estimated that unreported crashes in the U.S. account for up to 20% of traffic injuries requiring hospitalization, up to 50% of traffic injuries that do not require hospitalization, and up to 60% of all property damage only crashes. Blincoe *et al.* (2002) provided more recent estimates of the distribution of reported and unreported injuries in this country over eight severity levels, with estimates of under-reporting ranging from slightly less than 50% for PDO crashes to 0% for fatalities.

Although not often mentioned in the literature, it is plausible that under-reporting introduces other forms of bias as well. For example, crashes involving older or less valuable vehicles may be relatively less reported. They may also be less reported in poor or rural locations or, conversely, in very developed regions with a fast-paced lifestyle (where the people involved may not have time to wait for a police officer to arrive and record the crash). Undocumented drivers may attempt to avoid the official attention drawn by a crash report.

The general issue of crash under-reporting was addressed, through the application of observation weights, in the project's work on occupant-based injury severity models. However, some of the project work involved models of crash counts, and adjusting such data for under-reporting is not straightforward. Correction using observation weights is not feasible, since this ignores the discreteness of the basic data. Imputation methods may be of use here, but their possible application in this context appears to be totally unexplored.

2.7.1.3 Imprecise and Inaccurate Recording of Traffic Data

Many analyses of traffic safety relate the crash experience observed on a roadway to its traffic characteristics. A vehicle's exposure to crash risk is clearly related in some way to the number and type of its interactions with other vehicles. Information on roadway traffic characteristics is thus an important component of a traffic safety database.

Unfortunately, there are a number of problems with the data produced by traffic data collection programs, as routinely conducted, for example, by state DOTs. These programs are designed to produce estimates of traffic variables (volumes, composition, VMT, growth rates, etc.) at a level of accuracy sufficient for the needs of highway system management, operations and planning, but not necessarily for scientific research into traffic safety. Speed data are not routinely collected by most agencies.

Traffic data collected at a statewide level are generally produced by a system consisting of a few automatic traffic recorders permanently installed on major roadways, plus a larger number of less accurate counters that are moved from location to location, typically gathering traffic data at each location for a few days. A given location is typically re-visited at relatively long intervals, say every few years. Traffic volumes and other measures are estimated from the raw data collected by this program but, as indicated, are subject to significant estimation error. Moreover, they are typically only available for relatively long time intervals: a year, season or month. Davis (2000) discussed a Bayesian approach based on Gibbs sampling that accounts for the error in traffic volume estimates when computing crash rates.

The increasing prevalence of freeway management systems (FMS), with dense networks of traffic data collection devices deployed over the major roadways of an urban area, is generating a large amount of relatively detailed traffic data. The FHWA's Archived Data User Service (ADUS) provides a repository for storing and accessing this important data. Such data can be much more useful for research purposes than the data produced by a statewide program. In many cases, however, the raw data produced by an FMS is temporally aggregated, in large part to reduce data storage requirements. Traffic data actually collected over relatively brief intervals (a few tens of seconds, say), is often aggregated to intervals of several minutes or longer when stored. This obscures the temporal details of traffic flow characteristics.

2.7.1.4 Heterogeneity Bias and the Presence of Multiple Confounding Factors

A large number of factors may affect traffic safety. Any particular study may only be able to consider a subset of these factors because of data or study resource limitations. If the factors not considered in an analysis vary significantly over the observation frame, their effects on traffic safety may be *confounded* with those of the factors being studied.

Panel data, consisting of repeated observations over time ("time series") of a set ("cross section") of objects of interest (for example, a compilation of multiple years of crash data of all states, or of a set of roadway segments), are subject to a particular form of confounding. *Heterogeneity bias* is said to exist when unobserved factors systematically affect different cross sections or time slices of a data panel. In the presence of such problems, an analysis may wrongly impute to the included factors some effects that are actually due to the confounding factors, thus resulting in an incorrect estimate of the true impact of the studied factors (Karlaftis and Tarko, 1998).

One of the difficulties in drawing conclusions about the safety impacts of the 1987 NMSL relaxation, for example, is that a number of other important safety-related factors were changing during roughly the same time period: seat belt and alcohol-related laws, for example. The effects of these other changes must be disentangled from those of the speed limit changes occurring then in order to draw valid conclusions about their respective efficacies.

The following list indicates some of the factors that have been proven or hypothesized to affect traffic safety, and so may confound analyses that omit them:

- Demographic changes. The population overall is aging, and the driving population includes increasing numbers of older drivers. Similarly, it is well known that the crash propensity of young drivers is higher than average. Male and female drivers also have different crash propensities. A change in the age and gender makeup of the driving population would be expected to affect traffic safety statistics. Traffic safety studies involving observations at different times should account for the changing composition of the driving population.
- Changes in the level, pattern, distribution, scheduling and purpose of travel. The amount of automobile tripmaking clearly affects crash risk exposure. Changes in the pattern and distribution of travel (shorter *vs.* longer trips, urban *vs.* suburban *vs.* rural trips, trips on high-type *vs.* other roadway facilities) may also affect exposure. Crash rates in daytime and nighttime conditions are different so, other things equal, a change in the scheduling of travel would be likely to affect traffic safety (Chu, 1999). Trips for different purposes may involve different vehicle occupancies and greater or lesser driver familiarity with the roadways.
- Infrastructure improvements. Although Noland (2003) has argued that infrastructure improvements overall do not account for observed changes in U.S. crash rates over the period 1983-1997, significant changes in the design of a particular facility may have a significant effect on its safety performance and should presumably be taken into account.
- Vehicle and vehicle mix changes (type, weight, characteristics). Tay (2003) found that increases in the number of cars and buses in the overall vehicle population tend to reduce the total number of fatal crashes, whereas increases in the number of motorcycles, trucks, SUVs and vans increase the number of such crashes. Vehicle weight is a strong determinant of crash severity (Bédard et al., 2002). Vehicle crashworthiness has generally improved through improvement in structural design (crumple zones) and passenger protection (air bags). Even factors such as vehicle color have been shown to have statistically significant effects on individual crash risk (Lardelli-Claret et al., 2002; Furness et al., 2003).
- Seat belt, child restraint and young driver laws. Statistically significant differences in crash experience have been found between areas with primary enforcement (motorists can be stopped for not wearing a seat belt) and secondary enforcement (non-usage can only be sanctioned if a vehicle is stopped for some other reason). (Noland, 2003).

- Alcohol-related laws, including the maximum legal blood alcohol content (BAC), and the minimum legal drinking age.
- Driver education and public traffic safety awareness campaigns.
- Emergency response and medical treatment improvements. Improvements in the timeliness and quality of emergency response services, and in the hospital treatment of crash victims, are likely to affect the fatality/injury distribution of victims (Noland, 2003).
- Police enforcement differences, including the hypothesized shift in resources away from enforcing speed limits on interstates towards other roadway classes and other types of enforcement activities such as DUI (Lave and Elias, 1994; Greenstone, 2002).
- Weather variability.
- Secular trends other than those identified above.

2.7.1.5 The Ecological Fallacy

It has been known for a long time (e.g. Robinson 1950) that when detailed data is aggregated, the aggregate data may exhibit spurious relationships that differ substantially from the true relationships present at the detailed level. Correlations between variables may appear in the aggregate data where there are none in the underlying data and vice versa, or the direction of correlations may be reversed. Conclusions that are drawn about disaggregate relationships from analyses of aggregate data may thus be invalid. This is called the *ecological fallacy*.

In the context of traffic safety analyses, this discussion implies that the relationships observed between the mean speed, speed variance and crash statistics of large numbers of vehicles, such as annual summaries by road class or geographic area, may be completely different from the actual relationships between speed, speed variability and crash risk that exist at the level of individual vehicles. Note that the individual-level relationships are the ones relevant to tasks such as prediction and policy analysis, since the overall response to a change will be a result of the combined outcomes of individual responses.

Rodriquez (1990) and Davis (2002) illustrated how the aggregation of speed and crash data invites an ecological fallacy in safety study results. Rodriquez (1990) provided empirical evidence for the "variance kills" theory while assuming a monotonic increase in a driver's likelihood of fatal crash involvement with speed.

Davis (2002) demonstrated the ecological fallacy by showing that a positive correlation between aggregate crash rate and speed variance will indeed be exhibited when individual crash risk increases with speed variance, but also for a wide variety of relationships between individual crash risk and speed (including increasing, decreasing and U-shaped functions) that are completely independent of speed variance. It follows that no valid conclusion about the underlying relationship between individual crash risk and speed variance can be drawn from the observation of an aggregate correlation between crash rates and speed variance.

2.7.1.6 Site Selection Bias

Because of the inherent variability and independence of crash occurrences, a site that experiences an unusually high number of crashes in one time period is likely to have fewer crashes in subsequent periods. Hauer (1997) recognized this as an example of the famous "regression-to-mean" phenomenon.

The decision to implement safety-related treatments at a roadway location is generally taken because of recent high crash counts at that location. As noted by Harwood et al (2000), sites selected for a safety treatment on this basis will tend to experience fewer crashes in the period following the treatment, regardless of its efficacy. If such sites were then used to evaluate the safety effects of the treatment, it would not generally be correct to attribute safety changes entirely to the applied treatment. This is called site selection bias.

In particular, if sites are selected for speed limit changes based on their recent crash history, one must be very careful in drawing conclusions regarding the short-term safety impacts of the speed limit change. Davis (2000) argued that the mechanism by which sites are selected for treatment should be taken into account in modeling traffic safety effects, and concludes that there is presently no model estimation method that can be applied, without knowledge of the treatment selection logic, to estimate consistently the treatment's crash reduction effect.

2.7.1.7 Model Specification Issues

Linear regression models

These models posit a straight-line relationship between a dependent variable to be explained, and a set of explanatory, or independent, variables. The dependent variable is assumed to be continuous and able to assume both positive and negative values. It is assumed that the independent variables are accurately measured. Effects of unobserved variables and randomness in the data generation process are represented by an additive random error term, which is assumed to be independently and normally distributed across observations, and uncorrelated with the explanatory variables.

Linear regression and its various generalizations have been the workhorses of conventional statistical modeling for many years, and software packages to estimate such models are widely available.

Poisson, negative binomial models and their zero-inflated versions

Crash counts or frequencies are, by their nature, non-negative integers. Linear regression models are not generally able to accommodate this constraint on the dependent variables. Consequently, a significant amount of traffic safety research has been conducted using Poisson or negative binomial regression models, for which the outcome variables are, by definition, non-negative integers.

Poisson models have been proposed in many fields to represent the frequency of occurrence of events that are, by their nature, relatively rare; it thus is a logical candidate for use in crash occurrence modeling. Because of the mathematical form of the Poisson probability mass function, the mean and variance of Poisson-distributed random variables are necessarily equal. Since crash data do not necessarily exhibit this property, researchers have frequently turned to negative binomial models, which are similar to Poisson models but allow variances that are higher than the mean (over-dispersion).

It has been noted that actual crash data often exhibit a much higher number of zero-crash observations than would be expected from either a Poisson or a negative binomial generating process. One possible explanation, as noted above, is that crashes, particularly less severe ones, are systematically under-reported. Another explanation is that the data reflect the crash performance of a mixture of road types, some extremely safe (with a high probability of zero crashes) and some less so (for which the crash count distribution is adequately represented by a discrete distribution such as the Poisson or negative binomial). A number of researchers have utilized zero-inflated Poisson (ZIP) and negative binomial (ZINB) models to analyze data with high numbers of zero crash counts; these models treat the zero-observation state differently from a state with positive observations (Shankar et al., 1997).

<u>Fixed and random effects models</u>

Panel (time series of cross-sections) datasets provide rich opportunities for deep statistical analysis but, as mentioned above, are subject to biases resulting from unobserved factors that vary systematically across different observational units (e.g. states or roadway segments) or in time. A standard way of accounting for these unobserved factors is to include model terms that indicate the particular observational unit and/or time interval to which each data point belongs. The coefficient estimates associated with these terms should then capture the overall effect of the unobserved factors.

The statistical analysis of these terms can be handled in two ways. In *fixed effects* models, the available observations are assumed to represent the entire population. The coefficient estimate for the term is then a definitive statement of the average effect on the outcome associated with belonging to a particular observational unit or time interval. For example, in an analysis of state-level safety outcomes using time series data for each of the 50 states, a fixed effects model would be appropriate. In *random effects* models, the observations in the panel are assumed to be a sample from a larger population. In this case, the coefficient estimate for the term then reflects both the effects of the applicable unobserved factors, as well as the sampling properties that produced the observations. For example, a random effects model might be appropriate if the dataset consisted of time series observations of a random sample of roadway segments.

These two model types are treated somewhat differently in the estimation procedure. In practice, it is not always clear which of the two model types is more appropriate in a given situation, although a statistical test due to Hausman et al. (1984) can be used to evaluate alternative specifications.

<u>Functional specifications</u>

Hauer (2004) has noted that statistical modeling is often necessary in studies of road safety, but that it is also very difficult. He recommended that the following three questions be addressed before undertaking a traffic safety modeling exercise:

- which variables should be controlled in the model?
- in what form (e.g. additive, multiplicative) should the variables be included in the model?
- will the variables in the model appropriately represent their effects?

To guide the development of statistical road safety models, Hauer proposed several modeling principles.

First, the model should at least include two parts: additive and multiplicative. The purpose of the additive part is to control for point factors, such as driveways and ramps, while the purpose of the multiplicative part is to account for the effect of factors that apply over a stretch of road, such as lane width and median type.

The functional building blocks of the model should not be restricted to commonly used forms such as linear, logarithmic, and exponential. Indeed, Hauer argued that a more appropriate specification for a traffic safety performance measure Y would have the following form:

$$Y = (\text{Scale parameter}) \times \left[(\text{Segment length for prediction}) \times (\text{Multiplicative portion}) + (\text{Additive portion}) \right]$$
$$\text{Multiplicative portion} = f(\text{Traffic flow}) \times g(\text{Should type}) \times \cdots$$
$$\text{Additive portion} = h(\text{Traffic flow, \#driveways}) + i(\text{Traffic flow, \#short bridges}) + \cdots$$

Establishing a complete model specification should proceed in an exploratory fashion, adding one part after another. Of course, the model should be re-estimated after adding each new factor, typically using least squares or maximum likelihood estimation methods.

To illustrate his ideas, Hauer derived a maximum likelihood function based on the assumption that crash counts on one piece of segment follow a Poisson distribution with the mean $Y\theta_i$. Y is determined from an equation of the form described above, and θ for each segment follows a Gamma distribution with mean 1 and variance $1/\varphi_i$, where $\varphi_i = (\text{Segment length}) \times \varphi$. These assumptions lead to the following log-likelihood function.

$$\ln(l) = \sum_{\forall i} \ln(l_i) = \sum_{\forall i} \left\{ \varphi_i \ln \varphi_i + \left[\sum_{j=1}^{n_i} a_{ij} \ln(Y_{ij}) \right] + \ln\left[\Gamma(a_i + \varphi_i)\right] - \ln\left[\Gamma(\varphi_i)\right] - (a_i + \varphi_i)\ln(Y_i + \varphi_i) \right\}$$

where $a_i = \sum_{j=1}^{n_i} a_{ij}$, $Y_i = \sum_{j=1}^{n_i} Y_{ij}$, a_{ij} is the observed crash count on road segment i in time period j and Y_{ij} is the average of the mean crash frequency on road segment i in time period j for an imaged population of road segments with the same measured attributes as road segment i, but differing in many other attributes. As usual, the parameters β and φ are estimated by maximizing the above log-likelihood function.

<u>Choice of dependent variables</u>

Traffic safety can be measured in terms of crash frequency (e.g. counts per year) or crash rates (e.g. crashes per million vehicle-miles of travel [VMT]). A change in crash rate could be due either to a change in the prevalence of crashes, or to a change in the amount of travel (or both), and so is ambiguous. Researchers frequently prefer to use crash counts as dependent variables, controlling for the effects of changes in risk exposure by incorporating traffic measures as explanatory variables.

Models may focus on overall crash statistics, or may differentiate them according to their characteristics. Crash severity is commonly distinguished in terms of fatality (where a fatality is considered crash-related if it results from injuries sustained in a crash and occurs within a certain number of days after the crash), different injury levels, and property damage only. Differences over time between fatal and non-fatal crash counts or rates may reflect the quality of emergency response and hospital care better than the efficacy of road safety treatments. Consideration of crash type may also important since the causal factors that influence, for example, roadway *vs.* roadside crashes may be different (Shankar et al., 2003).

Recent studies have focused on the differing effects of traffic safety policies by crash victim type. Dee and Sela (2003) found, for example, that the post-NMSL repeal speed limit increases increased fatality rates among women by approximately 9.9%, but had small and statistically insignificant effects among men. They also found that the changes significantly increased fatality rates among the elderly and among women aged 25-44. Studies that consider only overall fatalities or injuries may miss differential effects of this type.

Choice of explanatory variables

Models should incorporate some measure of the crash risk that drivers in a sample are exposed to. This is commonly captured through use of variables such as VMT. To the extent that different vehicle types affect safety performance differently (Tay, 2003), exposure variables should include information about traffic composition by vehicle type. Similarly, to the extent that different traffic stream speed characteristics affect safety differently, speed-related variables should be included.

In more disaggregate modeling efforts, data that describe the characteristics of the roadway infrastructure and its operating environment may need to be included. Vehicle characteristics affecting crashworthiness or crash involvement propensity may need to be described. Similarly, in view of the different crash histories of different driver groups (e.g. young or elderly drivers), descriptors of the driving population may be needed. Finally, it may be important to include environmental descriptors, such as weather conditions at the time of crash, again depending on the level of detail of a particular model.

2.7.2 Methodological Approaches

Various statistical methods have been used to investigate the safety impacts of roadway design and traffic policy changes. These include different types of before-after studies, classical regression models and Bayesian methods. Most safety modeling results reported in the literature rely on classical methods and these methods are also used for this study. This section considers the other two approaches largely for purposes of comparison.

2.7.2.1 Before-After Studies

Before-After studies are generally conducted on sites where an improvement or “treatment” has been undertaken (thus the name “Before-After”). They are easy to understand and can be an efficient method for evaluating the safety effects of specific roadway treatment (where a treatment may be, for example, a change in speed limit or a geometric improvement of the road). Hauer (1997) discusses how the ideal Before-After study should focus on two measures of roadway safety performance in the after period: the actual performance following the treatment, and what the performance would have been if the treatment had not been applied. He splits the ideal Before-After study into four steps:

- compute λ and predict π
- estimate $VAR(\hat{\lambda})$ and $VAR(\hat{\pi})$
- estimate δ and θ
- estimate $VAR(\hat{\delta})$ and $VAR(\hat{\theta})$

where λ is the observed safety performance (e.g., crash count or crash rate) of the *treated* roadway in the 'after' period; π is a prediction of what the performance in the 'after' period would be if no treatment were applied; and $\delta \doteq \pi - \lambda$ and $\theta \doteq \lambda / \pi$ are two variables commonly used to describe safety performance changes due to a treatment. (For example, δ may be the average reduction in fatal crashes per million VMT at the site, and θ could indicate the fraction of crashes one could expect from the treated roadway relative to the untreated roadway.) The objective of most observational Before-After studies is to develop estimates $\hat{\delta}$ and $\hat{\theta}$ of the true δ and θ. The variance (or uncertainty) associated with these estimates is also key, since these may be more or less precise; thus $VAR(\hat{\delta})$ and $VAR(\hat{\delta})$ should ideally also be determined.

Successful use of this approach depends on accurate prediction of the performance without treatment and consistent comparison to the measured performance with treatment. Unfortunately, it is not easy to precisely predict the performance without treatment.

Most Before-After studies are "naïve" in that they look only at crash counts or other performance indicators before and after the treatment, neglecting a host of other variables (e.g., weather, traffic densities, enforcement, driver characteristics) that may change decisively between the before and after periods. In such cases, one cannot tell which portions of any change in safety attributes are properly attributable to the treatment. At a minimum, Hauer (1997) recommends accounting for traffic flows/roadway use, by working with crash *rates*.[5] However, most variables (such as weather changes) remain outside this modified approach, still limiting one's ability unambiguously to attribute safety performance changes to treatment. He also suggests using a comparable group of *un*treated roadways, to track and compare safety performances. However, in practice it generally is quite difficult to find comparable roadways for comparison, particularly if the decision to "treat" a roadway is based on some noted deficiencies[6].

Another issue is the appropriate definition of the 'before' period. This can be crucial to successful prediction of safety performance in the 'after' period without treatment. More data is better in offering a reliable prediction; this will help negate the effects of random variations in crash occurrences recent high crash counts, particularly in cases where sites are selected for treatment based on such data.

2.7.2.2 Classical Regression Models

Regression models seek to elucidate the relationship between response variables, such as crash rates and speed choices, and a variety of explanatory variables. In principle, classical regression models can predict the marginal effects of all control variables. In order to do so with statistically significant results, however, many observations are needed (for example, on the order of at least 10 observations for every control variable); a single before-after observation will not provide enough data for statistically significant results.

Many published research works investigate crash counts, crash severity, speeds and other variables important to this project using classical regression and related approaches. These

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[5] This approach implies a proportional relationship between safety performance and flow or use of the roadway, which may not be the case. But, for marginal crash changes in sites where congestion does not change substantially from the before to after period, this is probably an acceptable approach.
[6] The comparable roadways would share such deficiencies and would likely be slated for treatment as well.

include works by Shankar et al. (1997) and Abdel-Aty and Radwan (2000) on the topic of traffic crash counts; and by O'Donnell and Connor (1996), Kockelman and Kweon (2002), and Kweon and Kockelman (2003) on the topic of traffic crash severity.

2.7.2.3 Empirical Bayesian Methods

The basic alternative to classical statistical approaches is Bayesian statistics. Bayesian statistics is "subjective" in that all parameters of interest are assumed to come from a *distribution*, rather than being fixed or single valued. One can use a Bayesian approach for ordinary regression models by searching for the *distribution* of the parameters rather than unique parameter values. Hauer (1997, 2002) and Harwood et al. (2000) are prominent users of Bayesian methods in roadway safety analysis and modeling. Hauer (1997) developed and applied an Empirical Bayes method for traffic safety analysis, and this method is central to Harwood et al.'s (2000) Interactive Highway Safety Design Model (IHSDM) modeling effort.

In its application to traffic safety analysis, the Empirical Bayes method combines predictions of roadway safety performance with and without a safety treatment (e.g., a speed limit or design change) in order to eliminate any regression-to-mean biases that are present.[7] The method results in a minimum-variance unbiased estimator, regardless of the underlying functional form. (Hauer 1997) The post-treatment expected safety performance of a roadway (or intersection, for example) is a weighted average of model-predicted and observed measures, where the weights recognize the mean and variance of safety performance estimates obtained from the predictive model (or from roadways with similar characteristics). Weights on the model predictions are calculated as follows:

$$w = \frac{1}{1 + \frac{Var(\hat{\lambda})}{E(\hat{\lambda})}}$$

where $\hat{\lambda}$ is the model-predicted performance value after the treatment. Less weight is given to model predictions when the variance of the model estimates is high.

The Empirical Bayes estimate then is the combination of the model-predicted and actual/observed, after-treatment performance values:

$$\lambda^* = w\hat{\lambda} + (1-w)\lambda_{obs}$$

In order to develop the Interactive Highway Safety Design Model (IHSDM) base models for performance prediction, in the form of crash rates on rural two-lane highways, Harwood et al. (2000) used negative binomial regression[8]. The resulting base crash-rate estimates are used in the Empirical Bayes equations. In its current form, the model controls for total traffic volumes

[7] Hauer (personal communication, June 2003), feels that his Empirical Bayes performs particularly well when sites are chosen for treatment because of their past safety performance (i.e. in the presence of site or treatment selection bias.)

[8] Hauer (personal communication, June 2003) also notes that his experience when applying the negative binomial assumption in his analyses has been satisfactory to date. The weight function's variance-to-mean term is then simply the overdispersion parameter that characterizes this distribution.

and various geometric features (such as driveway densities and lane widths) but does not recognize other factors, such as traffic density, vehicle type, weather and traffic regulations. Moreover, its accident modification factors (AMFs) are determined based on expert judgment, which involves subjectivity and perhaps biases.

2.8 Non-Safety Impacts of Speed Limit Changes

2.8.1 General Approaches

In broad terms, non-safety impacts of speed limit changes may include effects on environmental, social, economic and/or commercial conditions as a result of a speed limit change. Not surprisingly, the literature on these impacts is dispersed among a number of different technical fields. Unfortunately, generally applicable conclusions are frequently lacking.

Kamerud (1983) provided an early analysis of the range of possible impacts of the NMSL. He proposed a relatively straightforward analysis and benefit-cost evaluation framework for quantifying the impacts of a speed policy (for example, speed limits by road classification and year). His analysis considers impacts using three different criteria: money, lives and time.

In Kamerud's framework, a speed limit policy directly affects vehicle speeds and crash experience. Speeds, in turn, affect the travel times of cars and trucks, as well as their fuel consumption. The crash experience affects the number of nonfatal and fatal crashes. The predicted car travel time is retained as one measure of the speed policy impact. The costs of nonfatal and fatal crashes, of fuel consumed and of truck travel time are combined into a second, monetary measure of the speed policy impact. The number of fatalities is retained as the third measure of the policy impact. These three measures can then be combined into an overall assessment of the social cost of a speed limit policy, permitting policies to be compared and enabling tradeoff analyses to be conducted.

Several studies have applied cost-benefit analysis to investigate the net effect on society of increased speed limits. For example, Miller (1990) incorporated four major effects attributable to raising speed limits: travel time savings, fatality increases, nonfatal injury increases, and traffic delays.

Similarly, Jondrow et al. (1983) sought to determine a socially optimal speed limit within a welfare maximization framework, assuming that actual driving speeds change in step with speed limits. Their approach identified the optimal speed limit as that which equated private marginal benefit with total social marginal cost (consisting of the private marginal cost plus the external costs of crashes and fossil fuel depletion). The calculations considered the income transfer from U.S. citizens to the oil-producing countries as one of the externalities. The analysis found that the optimal speed limit was higher than 55 mi/h.

In related work, Lee (1985) investigated the idea of optimal speed limits from a perspective of policing and evasion costs, but did not include other costs such as pollutant emissions, property damage and loss of life.

Elvik (2001) discusses quantifiable items that are generally considered in the evaluation of road investment projects in Norway. A subset of these is relevant to the analysis of non-safety speed limit impacts:

- travel time, by trip type;
- travel time reliability, by trip type;
- vehicle operating costs, by vehicle type;
- crashes, by severity level;
- traffic noise, by level and location;
- air pollution, by pollutant type.

While the present NCHRP study has not conducted comprehensive cost-benefit or similar analyses of alternative speed limit policies, the framework established for such studies can be useful for organizing knowledge about the relationships that are of interest here (Rune, 2001).

It should be kept in mind that in many states the portion of statewide VMT produced on uncongested high-speed roads is a relatively small fraction of the total. Changes in speed limits on high-speed roads are likely to have a very limited impact on traffic on the remainder of the roadway system. The type of traffic most likely to be affected by such speed limit changes is long distance traffic on rural facilities, such as that due to interstate truckers and vacationers.

2.8.2 Travel Time and its Reliability

To the extent that speed limits (rather than congestion, for example) constrain prevailing highway speeds, there is clearly an inverse relationship between speed limits and travel times.

Numerous studies have attempted to determine appropriate equivalent monetary values per time unit ("value of time") for use in project evaluation and related analyses. Application of a value of time to the travel times experienced in different situations (e.g. with different speed limits) allows calculation of the monetary value equivalent to the time difference.

For trips by passenger vehicles, it is generally accepted that the value of time is related to the trip purpose, the traveler's income, and a variety of other factors. In the absence of specific studies, standard values (expressed either in monetary units or, for example, as a fraction of the average hourly wage rate) are commonly applied. An individual's value of time is, in economic terms, the marginal rate of substitution between time and money, other things remaining equal. A number of issues remain unresolved such as, for example, the appropriate valuation of travel time savings that are so small that the time made available has little use for other purposes.

There is less consensus on values of time appropriate for trips by commercial vehicles. The value of time is clearly related directly or indirectly to the value of the merchandise, the time sensitivity of the delivery, and the driver's payment policy. Again, standard values are typically applied for project evaluation purposes.

A distinction between the short-term and long-term commercial vehicle value of time may be useful in this context. In the short term, the time saved by a truck traveling at higher speeds may not have economic value if the truck cannot use the extra time for some productive purpose. (This is similar to the problem of valuing small savings in personal travel time, mentioned above.) In the longer run, however, firms are likely able to re-arrange their production and transportation processes ways that take account of systematic changes in travel times, and reduce such slack. In this sense, speed increases are likely ultimately to result in increased productivity of commercial vehicles and the businesses that use them. This effect is only partially captured in the standard values of commercial vehicle travel time mentioned above, but a more accurate assessment of these benefits is highly context-specific.

As part of its study of NMSL repeal impacts, the New York State Department of Transportation conducted interviews with the New York State Motor Truckers Association (see Section 3.2). The trucking association was asked if its members felt that changed speed limits would affect their operations or finances; the answer was negative.

The US DOT (1997, 2003) has prepared standard values of time for application in transportation project evaluation studies in this country. The most recent values of time recommended for passenger travel by surface modes are $11.20/h for local travel and $15.60/h for intercity travel, all trip purposes combined (US DOT 2003).

Speed limit changes can also affect travel time reliability (e.g. variance) though their impact on random crash-related delays, and possibly through changes in the inherent variability of traffic flows at different speeds. Explicit recognition of the economic value of travel time reliability is relatively recent. However, reliability clearly has a value. If personal or commercial travelers hedge their departure time decisions by leaving early to allow for the possibility that a trip might take longer than expected, the time taken in this way frequently cannot be used for other activities and so has an opportunity cost. Similarly, if an arrival that is earlier or later than expected results in wasted time or disrupted plans, again the (un)reliability of travel time can be said to have a cost. Using stated preference surveys, Small *et al*. (1999) have estimated values of time and of time reliability for both passengers and freight carriers.

Haight (1994) argues for considering travel mobility (travel time and its reliability) and traffic safety as two related outputs, jointly produced by the overall functioning of the road system.

2.8.3 Vehicle Operating Costs

At issue here are the costs of owning and operating motor vehicles, and in particular the way in which these costs vary with speed. Although some discussions treat travel time-related costs as an operating cost component, time costs are treated separately above; this section considers only the costs associated with the physical resources involved in vehicle ownership and operation.

Vehicle operating cost (VOC) models are components of a number of standard transportation project evaluation tools used in this country. These tools include HERS-ST (Highway Economic Requirements System – State Version) (FHWA 2002), STEAM (DeCorla-Souza and Hunt, undated), MicroBENCOST, StratBENCOST, and others. Most of these tools rely heavily on original data on consumption relationships for different vehicle types obtained by Zaniewski *et al.* (1982), with updates to account for changes in technology since the time of that study.[9,10] Unless otherwise noted, the remarks below do not refer to any particular VOC model system.

[9] Bein and Biggs (1993) argue that vehicle technology has changed so much since the early 1980s that a new study, rather than simply an update, is required.

VOC models generally attempt to account for the effects on operating costs of a variety of factors – such as roadway grade and curvature, pavement condition – that are not relevant to the discussion here; the focus is on the variation of operating cost with speed. Speed-related variables considered by most VOC models include speed itself and speed change cycles; the latter can be related to the variance of individual vehicle speeds on a roadway, which in turn influences and is influenced by the variance of speeds between vehicles. One standard cost calculation approach proceeds by first determining operating costs at a constant average speed, and then adding "excess" costs due to speed change cycles around that average. The calculations are generally done on a per-mile basis for each relevant vehicle type, with the unit results multiplied by roadway length and vehicle mix to obtain total operating costs as appropriate.

For a given vehicle type, the operating cost per mile is built up from a number of cost component values. Cost components are generally divided into *running* and *fixed* costs.

Running costs are those, such as fuel, oil and tire costs, which directly result from the resources consumed by the operation of the vehicle. The per-mile cost values for these components are typically calculated by determining the actual quantity of resource consumed (e.g. volume of fuel or oil) per mile, then multiplying by the corresponding unit resource cost. The unit resource consumption rates generally vary with speed, so the effect of speed on these operating cost components is directly captured. Note that, for economic analyses, resource costs are provided net of transfer payments such as taxes or subsidies.

Fixed costs tend to relate more to the ownership than to the operation of the vehicle. Examples include time-related depreciation and vehicle license or registration fees (to the extent that these represent a charge for services provided public agencies and are not simply transfer payments). These cost components are considered "fixed" in the sense that they are essentially independent of vehicle use. To determine an equivalent per-mile value, the estimated cost of each of these components over a given period of time (a year or the vehicle lifetime) is prorated over the corresponding vehicle mileage.

Some operating cost components, such depreciation, are most appropriately treated as a combination of a fixed cost related to the passage of time (a vehicle loses a certain value every year even if it sits in a garage) and an amount that varies with use (other things equal, a vehicle with more mileage has less value; moreover, greater use brings a greater likelihood that a vehicle will sustain damages that further reduce its value). Vehicle maintenance costs are similar in having portions that are both variable and fixed with respect to use.

As noted, fixed cost components must be prorated over the corresponding mileage in order to obtain a per-mile cost. To the extent that speed affects a vehicle's annual or lifetime mileage, the prorated per-mile value for these components will also be affected.[11] The exact nature of the speed-mileage relationship has not been empirically established, and is quite likely different for private and commercial vehicles. The treatment of fixed costs in particular models or applications tends to rely heavily on the judgment of the model-builder or practitioner.

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[10] STEAM does not rely on the data collected by Zaniewski *et al*. Instead, it makes use of data collected by Caltrans during roughly the same time period as the work of Zaniewski *et al.* (Hatano *et al*., 1983; Cohn *et al.* 1992).
[11] A vehicle's rate of depreciation may also depend on the average speed at which it is driven.

In practice, the two largest components of total vehicle operating cost are fuel costs and depreciation. Although depreciation is a large component of total operating costs, its per-mile value is relatively (or perhaps completely) insensitive to moderate changes in speed, and so can generally be neglected in discussions of speed change impacts on operating costs.

A sense of the monetary magnitude of the speed effect on fuel consumption can be obtained by considering the HERS-ST relationships as a specific example. In HERS-ST, the fuel consumption of a vehicle at a constant "effective" speed (average driving speed computed by correcting estimated free flow speed for the effects of congestion and traffic control devices) is given by a mathematical equation, different for each vehicle type. Figure 2-1 below shows the constant speed fuel consumption rates calculated for a light duty vehicle (LDV) and heavy duty vehicle (HDV) on a flat, straight section.

It can be seen that the fuel consumption increases monotonically over the entire range of effective speeds considered, increasing by roughly 25% for LDVs and 10% for HDVs between effective speeds of 55 and 65 mi/h. For gasoline and diesel fuel prices of roughly $2/gallon and Federal and state taxes amounting to around 50 cents/gallon, this fuel consumption increase translates into an economic cost increase of roughly 1.9 cents/mile for both vehicle types.[12] Changes in fuel prices and/or taxes would, of course, directly affect this value.

It is known that, following a speed limit increase, average travel speeds generally rise by less than the full amount of the increase (see Sections 2.3 and 4.2). Roughly speaking, a speed limit increase from 55 to 65 mi/h might be expected to increase average travel speeds by about 4 mi/h on the corresponding facilities. In the general range of speeds considered here, this would translate into a fuel cost increase of around 0.8 cent/mi.

A report by Schneider (undated) on NMSL-repeal impacts in Louisiana investigated changes statewide fuel consumption following the repeal. Changes in both VMT and taxed fuel consumption were very small in the period 1996-1998. Schneider was able to detect a decrease of 0.2% in the statewide average fuel economy (mi/gallon) during the period; however, in view of changes in the fleet mix (increasing fractions of SUVs and light trucks) occurring at the same time, it was not possible to attribute with certainty this global decrease to the speed limit change.

The operating cost increase estimated above can be compared against the monetary value of the travel time saved by traveling at the higher speed. Using an average value of time of $15/h (US DOT 1997, 2003), the same 4 mi/h speed increase would result in a time savings of roughly 1.7 cents/mi.

It can be seen that, for this particular speed increase example, the value of travel time savings is roughly twice the amount of the increased fuel (or operating) cost. The relative magnitude of these two effects explains why some studies of the economic impacts of speed limit changes have chosen to ignore the vehicle operating cost variation resulting from the change (Reed, 2001), focusing exclusively on the travel time and other cost changes. The project's analysis of rational speed choice (Section 4.2.5) also decided to adopt this approach.

[12] Strictly speaking, the fuel cost calculation should include the effect on consumption of the speed change cycles that occur at each speed. However, the excess fuel consumption cost due to speed change cycles is similar at the two speeds, and so drops out in the cost comparison.

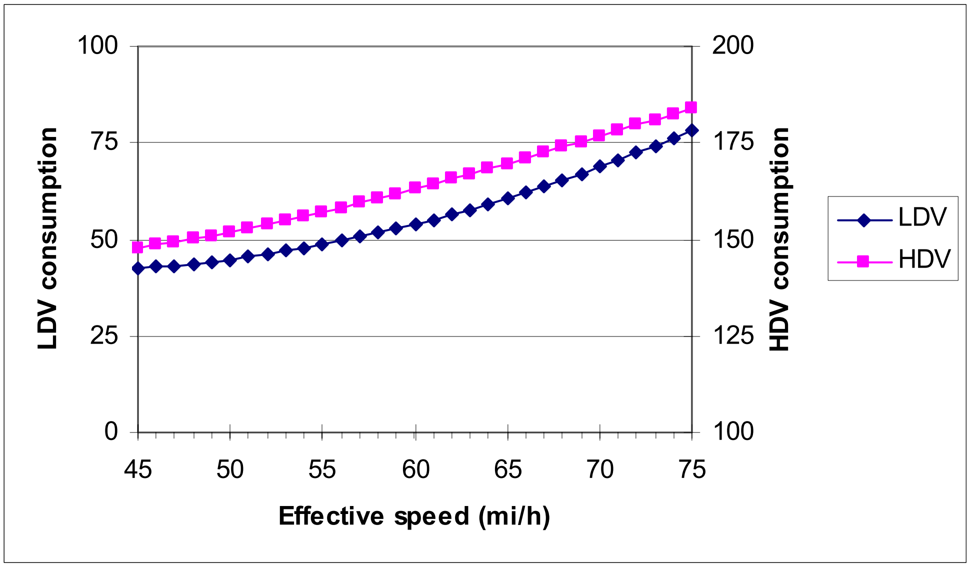

Figure 2-1 – Fuel Consumption at Constant Speed (gallons/1000 miles)

Notes: LDV is a medium/large automobile
HDV is a 3+ axle single unit truck
Consumption is calculated for a flat, tangent section with good pavement quality.
Source: HERS-ST v2.0 (FHWA, 2002)

2.8.4 Economic Cost of Injuries and Fatalities

Evaluation of the economic cost of injuries and fatalities resulting from motor vehicle crashes generally follows one of two alternative approaches.

The so-called *human capital* approach estimates the direct and indirect costs to individuals and to society as a whole from the impacts on the health status of those injured or killed in crashes. Individuals are viewed as producers and consumers of economic output. The value of their decreased production and consumption is included in the calculation of total cost. The resources consumed as a result of any injury or crash that might otherwise be used for increasing societal well-being are also counted in the total cost. Psychological or emotional costs, or valuation of pain and suffering, are not explicitly accounted for in the human capital approach unless they have measurable ramifications (for example, reduced work productivity or the cost of counseling services). This is the approach adopted, for example, in the official NHTSA analysis of motor vehicle crash impacts by Blincoe *et al*. (2002). Some controversy surrounds this method because it implies, for example, that low income people would have a correspondingly low value of life.

In contrast to this, the *willingness-to-pay* (*WTP*) approach attempts to value the change in well-being that would result from changing the risk of crash-related injury or death. This valuation is generally determined through survey methods such as revealed or stated preference surveys. Revealed preference surveys analyze the tradeoffs that people actually make when they are in situations involving a choice between more money and greater risk of injury or death. Stated preference surveys describe a hypothetical situation to survey respondents, and then ask a series of questions intended to elicit information about money/risk tradeoffs. Revealed preference surveys have the advantage of being based on actual behavior, but are limited to the situations that happen to present themselves in practice. Stated preference surveys are subject to a variety of response biases, but allow a researcher to explore in detail an individual's tradeoffs. Some statistical methods allow the two types of survey to be combined, and statistically exploit the advantages of each. Dionne and Lanoie (2004) discuss the WTP approach in detail, and review a number of studies that apply this approach.

2.8.5 Noise

Noise is defined as unwanted sound. Transportation-related activities are major producers of noise around the world. The literature review did not identify any useable references that analyze the noise impacts of speed limit changes.

Traffic volume, vehicle mix and speed are among the principal factors that affect the amount of noise produced by a stream of roadway traffic. Above 50 mi/h, the greatest source of noise is the tire-road contact (TRC). Below 20 mi/h, the noise generated by vehicle power units (engine, air intake and exhaust) tends to predominate. At intermediate speeds, traffic noise is produced by both of these. Acceleration and deceleration maneuvers can also contribute to the total amount of noise produced by a traffic stream.

The level of noise experienced at a particular location, however, is typically very context-sensitive. Noise levels near a road depend strongly on site characteristics, the built environment, and general environmental factors. It may not be possible to make generally applicable statements about this issue.

Following the NMSL repeal, New Jersey decided to adopt a staged approach to changing speed limits. During an initial period, it changed speed limits from 55 to 65 mi/h on roughly 500 miles of selected roadways around the state; and the impacts of these changes were monitored and analyzed prior to deciding whether to extend the higher limits to other portions of the roadway system. The (small) changes in speeds and traffic volumes following the speed limit change were used as inputs into a standard noise analysis model. It was determined that the noise level change resulting from the speed and volume changes would not be perceptible in the overall noise environment adjacent to the selected highways.

2.8.6 Air Quality

Pechan and Associates (1995) conducted a pre-repeal prediction of the effects on NOx emissions of the repeal. Based on a state-by-state analysis, they concluded that NOx emissions would increase nationwide by approximately 5% as a result of the repeal. The analysis applied the MOBILE5a air quality model, and considered both extreme and most likely speed changes expected to follow the NMSL repeal.

Air quality issues have sometimes been evoked as a reason for lowering speed limits, particularly in areas that do not attain the National Ambient Air Quality Standards regarding different category pollutants, and so are under risk of Federal sanctions. Speed limits set for such reasons are sometimes called *environmental* speed limits. Texas was one of the first states to apply such limits.

In 2000, Texas passed legislation authorizing the Texas Natural Resource Conservation Commission (TNRCC), the state environmental agency, to set speed limits in on selected roadways in non-attainment areas. In the Houston-Galveston area, speed limits on high speed roads were to be reduced to 55 mi/h beginning in 2002. There was considerable opposition to this decision by citizens and various groups, and the technical studies that underpinned the decision were scrutinized. A newer version of the EPA's mobile source emissions factor model (MOBILE) had been released, and was used to re-do the original analyses. It was found that the lower speed limits would produce less reduction in NOx and volatile organic compounds (VOCs) than was originally predicted, and that most of the reductions would be achieved from heavy duty vehicles. (These analyses assumed that drivers would fully comply with the new speed limits, and this assumption was also strongly questioned.) As a result of these factors, the TNRCC suspended the proposed implementation of the 55 mi/h limit, deciding instead to reduce pre-existing 70 and 65 mi/h limits by 5 mi/h for all vehicle types.

The New Jersey study of NMSL repeal impacts on selected roadways (mentioned in Section 2.8.5 above) also considered the air quality impacts of the observed changes in speeds and flows on the roadways following the speed limit change from 55 to 65 mi/h. A standard air quality model was used to predict these impacts. Increases of 0.20%, 0.90% and 1.15% were found in traffic-related emissions of volatile organic compounds (VOCs), nitrous oxides (NOx) and carbon monoxide (CO), respectively. The New Jersey study deemed these impacts to be "nominal", i.e. insignificant.

2.9 Effects of Differential LDV/HDV Speed Limits

The present project was tasked with examining the current state of knowledge regarding the safety impacts of differential speed limits. Observational data to investigate this question were not available to the project for analysis, so the task was performed through an examination of the relevant literature. Results of that examination are reported here.

The term *differential speed limits* (DSL) refers to the practice of requiring vehicles with certain size, weight or configuration characteristics to adhere to a lower speed limit than applies to automobiles. The lower limit may be 5, 10 or 15 mi/h less than the automobile limit. This is in contrast to *uniform speed limits* (USL), where all roadway vehicles are expected to comply with the same speed limit. Typically the vehicles affected by the lower limit are heavy duty vehicles (HDV) such as trucks, truck-trailers and tractor-semitrailers beyond a certain gross weight, although in some states the lower limits also apply to light duty vehicles (LDV) such as automobiles or light trucks when they are pulling a trailer. The summary here will refer generically to LDVs as cars and to HDVs as trucks, and will not generally examine regulations or studies pertaining to special category vehicles such as LDVs pulling trailers.

It should be noted that other practices affecting speed limits could also be characterized as differential speed limits. Texas, for example, allows cars to travel on rural interstate highways at 75 mi/h during the day, but limits speeds to 65 mi/h after dark (it also applies different speed limits to cars and trucks). Many states impose different limits on urban and rural interstates. Finland reduces speed limits on many roadway classes during the entire winter season, and this practice is reportedly under consideration by other Nordic countries. In a randomized experiment conducted in Finland prior to the official adoption of this policy, significant reductions in crash counts were found on the road sections studied (Peltola, 2000). Some

European countries change speed limits in real time based on prevailing traffic, weather or environmental conditions. The Netherlands has implemented a system of real-time speed *advisories* – driving speed recommendations based on prevailing traffic conditions, but with no obligation on the part of drivers to comply – as a means of delaying the onset of unstable traffic flow and so increasing roadway capacity (Smulders, 1990). Lee et al. (2004) investigated (through microscopic traffic simulation) the effectiveness of real-time changes in speed limits based on congestion measurements as a means of stabilizing traffic flows and reducing the potential for crashes. However, these various practices will not be further considered here. NCHRP Project 3-59, which is currently ongoing and due to complete in mid-2005, is examining the implementation issues associated with some of these.

DSLs have been in effect in various states since the construction of the Interstate Highway System, although the imposition of the NMSL had the effect of instituting a *de facto* USL across the country. Currently (2004), twelve states apply DSLs on rural interstates: Arkansas, California, Idaho, Illinois, Indiana, Michigan, Montana, Ohio, Oklahoma, Oregon, Texas and Washington State. In the European Union, heavy trucks are required to be equipped with speed governors that limit their speed to 90 kph (56 mi/h).

Arguments in favor of DSLs emphasize the differences in physical, performance and maneuverability characteristics of heavy trucks *vs.* automobiles, suggesting that at higher speeds trucks are less able to react effectively in a dangerous situation: reaction distance, stopping distance and other risk factors are increased at higher speeds. These arguments also note that crashes involving trucks, particularly at higher speeds, tend to be more severe. It is also sometimes argued that lower truck speeds result in fewer exhaust emissions and improved air quality. This was a key argument originally supporting the creation of environmental speed limits for both cars and trucks in Texas, and led to pressure to maintain low truck speed limits even as the low automobile limits were relaxed.

Arguments against DSLs point out that they introduce greater speed variance in the traffic vehicle stream, referring to the "Variance kills" theory discussed above. Differential limits tend to create more situations where cars want to pass a slower truck, but these cars may have restricted sight distance because of the truck's width, so the overtaking maneuver may be more dangerous than usual. Moreover, the low pressure created by the passage of trucks through the air may tend to draw cars closer to them during passing maneuvers, thus increasing the danger of a collision. DSL opponents rebut the pro-DSL argument that trucks are intrinsically less safe by pointing out that trucks' heights provide their drivers with improved visibility, so they may in fact have more time to react to a dangerous situation than automobile drivers. Another argument against DSLs refers to the possibility of spillover effects: commercial truck drivers may react to the DSL on an interstate highway by choosing to use alternative routes that, because of less stringent design standards, may not be as intrinsically safe as an interstate.

Past changes in DSL policy, either nationwide (the 1974 NMSL, the 1987 relaxation and the 1995 repeal) or at a state level, have created natural experiments that have been examined by researchers to investigate the safety impacts of DSLs. Many of these investigations are ably summarized in the recent synthesis report of Harwood *et al*. (2003). The following paragraphs concentrate on studies conducted roughly within the past decade.

In a recent study, Garber et al. (2003) and Yuan and Garber (2002) examined the rural interstate crash experience in nine states during the1990s, as a function of their auto and truck speed limit policies following the 1987 relaxation and the 1995 repeal of the NMSL. States were divided into those that maintained a USL; those that maintained a DSL; those that changed from a USL to a DSL; and those that changed from a DSL to a USL. Speed monitoring data were analyzed by applying ANOVA in before and after comparisons of states that changed policy, and in pre-repeal/post-repeal comparisons of states that did not; the latter analysis was conducted to determine whether significant changes in traffic speed characteristics occurred over time even without a policy shift. Speed characteristics included mean speed, speed variance, 85th percentile speed, median speed and speed limit non-compliance rates. Similar approaches were used to analyze crash rate data, including total, fatal only, read-end only, total truck involved, fatal truck involved, and truck involved rear-end crash rates. All data were derived from summary reports, aggregated to an annual basis and analyzed at a statewide level.

The study found that speed characteristics were generally unaffected by policies: for almost all states examined, the mean, 85th and median speeds tended to increase (although not always in a statistically significant way) over the decade of the 1990s, regardless of changes in USL and/or DSL policies. It also found that crash rates did not bear any notable relationship to the type of or changes in speed policies in the various states. In summary, the study found no significant relationship between USL/DSL policies and the speed and crash characteristics studied. It must be remembered, however, that the study worked with highly aggregate data, and that underlying relationships may be obscured or reversed as a result.

Earlier work by Garber and Gadiraju (1992) examined the effects in five states of DSL policies imposed following the 1987 NMSL relaxation; the study considered both speed and crash characteristics. The study did not find a significant difference in all-vehicle or in auto-truck crash rates among states that did and did not impose DSLs, although there was some evidence that a DSL may increase the frequency of some kinds of crash while reducing the frequency of others. The study did find that DSLs have a significant impact on truck speeds and on overall speed variance.

Harkey and Mera (1994) conducted another comparative study of USL/DSL impacts based on data following the 1987 NMSL repeal. Speed and crash data were collected from urban and rural interstate locations in 12 states employing both kinds of limits. Overall, the analysis showed no significant difference in number of crashes or crash severity with respect to the type of speed limit. However, the study found that truck-into-car crashes of all types occur more frequently in areas with USLs, while car-into-truck crashes are more frequent in DSL areas. Crashes in which trucks rear-ended cars were 57% more frequent in USL locations, while crashes where cars rear-ended trucks were 26% more frequent in DSL locations (although this result was not statistically significant). Greater speed variance was observed when the speed limit differential between cars and trucks was greater than 5 mi/h.

Rabjhandari and Daniel (2003) and Rabjhandari (2002) used ARIMA time series intervention analysis to examine the crash record of road sections where truck speed limits were increased to 65 mi/h from a lower level. Crash data were obtained for the 17-month periods both preceding and following the speed limit change. The data source consisted of individual crash records in an NJDOT database, aggregated to monthly totals. Models were developed for all crashes, truck crashes, and truck-car crashes. The analysis did not result in a statistically significant coefficient for the intervention parameter, although the ARIMA model with intervention parameter appeared to fit the post-increase data better than a model developed using only pre-increase observations. The interpretation of this finding is not clear.

In July 1998, Idaho imposed a 10 mi/h DSL for heavy duty vehicles over 26,000 lbs. The National Institute for Advanced Transportation Technology at the University of Idaho analyzed the first year of traffic speed and safety experience following this change (NIATT, 1999). The analysis considered monthly aggregate speed measurements from 17 automatic traffic recorders (ATRs) on interstate highways, taken during the periods approximately one year before and after the speed limit change. Crash statistics were compiled for the same highways. The study found small but statistically significant decreases in truck speeds following the speed limit change, and small but statistically significant increases in car-truck speed differentials. Car speeds were not affected, and the standard deviation of vehicle speeds (cars only, trucks only, and all vehicles) did not increase, indicating that the speed limit change did not significantly affect the variability of speeds. The study also found a significant increase in the proportion of trucks that violate the speed limit, but no significant change in total or truck-involved crash rates. However, the study recognizes that the low number of crashes present in the analysis dataset limits its conclusions.

Using state-level data, Neeley and Richardson (2004) estimated a random effects model to analyze the impact of different factors and policies on fatalities involving tractor-trailers. They found that increasing the truck maximum speed has a significant and positive effect on the fatality rate, but that the difference between auto and truck maximum speeds has no statistically significant effect *per se*. Put differently, they conclude that a policy of reducing the truck speed limit without changing the auto speed limit would have a favorable impact on fatalities.

In considering the above studies, it will be seen that most of them rely on aggregate data. As was discussed above, reliance on aggregate data can obscure the true underlying relationships, or can create the appearance of relationships that are not actually present in the individual level data and so lead to ecological fallacies. This caveat must be kept in mind when interpreting the published literature.

The state of Oregon recently conducted a study of issues related to proposed speed limit changes on interstates there (Monsere *et al*., 2004). The state currently enforces a 10 mi/h differential, but is considering a proposal to lower the differential to 5 mi/h. The study reviewed the published research literature on DSLs and concluded that “research on this subject has not demonstrated any definitive evidence that supports the safety case for or against differential truck speeds.” This is a fair statement of the current state of knowledge in this area.

2.10 Summary

This chapter has reviewed a wide range of literature related to the analysis and modeling of speed limit change impacts.

It considered general studies of the impacts of the NMSL imposition, relaxation and repeal, as well as more focused studies of speed limit effects on speeds and traffic safety. It also considered studies of non-speed limit policies that are directed at traffic safety, and of roadway design characteristics on travel speed. The chapter next reviewed the difficult methodological issues involved in the analysis of speed limit impacts, and examined the state of knowledge regarding non-safety impacts of speed limit changes, and of differential car/truck speed limits.

This review informed much of the project’s analytical work, described in Chapter 4, as well as its conclusions and recommendations, presented in Chapter 5.

3 Project Survey Results and Analysis

Two surveys were carried out and analyzed during the study.

The first was an internet-based survey of state DOTs, intended to obtain information from them on a variety of issues related to speed limits on high-speed roads. Section 3.1 discusses this survey, including its execution and results, as well as the conclusions that were drew from it.

The second was a limited telephone survey of state police or highway patrol agencies, intended to learn about agency responses to the NMSL repeal and, more generally, about their decision-making practices regarding the allocation of traffic enforcement resources. Section 3.3 discusses this survey.

As will be seen, one of the questions in the survey of state DOTs concerned studies that were performed around the time of the NMSL repeal to plan for and assess the impacts of the speed limit changes. A number of respondents provided references to studies that their Department had carried out or commissioned. These were obtained from the DOT and reviewed by the project. The reviews are also provided in Section 3.2 below.

3.1 Survey of State DOTs

The description of Task 2 in the project Scope of Work reads:

"*Conduct a survey to collect data on the experiences of state DOTs that have raised speed limits. This survey should be designed to collect information including, but not limited to, the following:*

- *range and magnitude of speed limit changes in the states;*
- *mileage and types of highways with raised speed limits;*
- *design and traffic engineering procedures used to determine if and where speed limits should be changed;*
- *legal limitations and other factors in the decision to raise speed limits;*
- *published and unpublished information summarizing the DOT's experience since raising speed limits;*
- *availability of before and after data on volume, speed, number of accidents, and accident rates; and*
- *willingness of the DOT to provide those data for the study."*

Section 3.1.1 below describes the steps that the study team carried out to prepare and execute the survey; Section 3.1.2 presents summaries of and extracts from the responses that were received; and Section 3.1.3 develops the conclusions that the team drew from these responses. A complete copy of the survey instrument is provided in Appendix A.

3.1.1 Survey Preparation and Execution

3.1.1.1 Preparation

The study team prepared a draft survey questionnaire that covered the data elements specifically identified in the project SOW, as well as others that were of interest to the study. In developing the questionnaire, a number of possible structures were considered. In the end, the team decided on a fairly simple approach that attempted:

- to establish the location and characteristics of speed limit increases on high-speed roads since the repeal of the NMSL in 1995;
- to identify available data, reports and studies relating to the speed limit changes and their impacts;
- to identify other available sources of data on traffic volumes and traffic safety;
- to understand the protocols and procedures for decisions relating to highway patrol deployments for speed limit enforcement; and
- to understand the protocols and procedures for decisions relating to speed limit increases, either across an entire class of highway facilities (e.g. rural Interstates) or on individual high-speed roads or road sections.

A basic issue had to be considered in designing the questionnaire: the answers to many of the questions potentially involved considerable quantities of data. A questionnaire that attempted to collect such data might be excessively unwieldy and, moreover, might dissuade respondents from completing the survey. In general, therefore, it was decided that the questionnaire would *not* directly ask for such data; rather, it would ascertain if the information existed and, if so, would ask how to obtain it at a later time, if necessary.

3.1.1.2 Execution

It was decided to administer the questionnaire via an Internet web site accessible using a standard web browser. Suitable survey respondents were identified in each state DOT with the help of the TRB State Representatives. The designated person was then contacted and asked to contact the survey team to obtain a password with which to access the survey web site. In order to ensure the largest possible response rate, team members repeatedly contacted the designated state DOT personnel over the course of approximately six months, using both email and voice mail for this purpose.

The web site home page offered basic information about the purpose and use of the survey instrument, and asks respondents to identify themselves. The questions were divided into sections, roughly corresponding to the types of data identified in the project SOW. In a particular web session, a respondent could choose to answer questions in any or all of the sections. Respondents could save a partially completed survey and return to it later. When the entire survey was complete, the respondent was thanked and the survey permanently saved. (A Microsoft Word file version of the survey was also made available to respondents who preferred to work offline; the completed questionnaire was then emailed to the study team.)

3.1.2 Presentation of Survey Results

Responses were eventually received from 33 states. The following table identifies the responding states and the main survey respondent in each.

Alabama	Mr. Timothy Taylor
Alaska	Mr. Kurt Smith
Arizona	Mr. David Duffy
Arkansas	Mr. Mike Selig
California	Mr. Craig Copelan
Connecticut	Mr. Robert Uricchio
Florida	Mr. Patrick A. Brady
Georgia	Mr. Keith Golden
Idaho	Mr. Lance Johnson
Illinois	Mr. L. W. Gregg
Indiana	Mr. John L. Nagle
Iowa	Mr. Tim Crouch
Kansas	Ms. Linda Voss
Kentucky	Mr. Duane Thomas
Louisiana	Mr. Peter Allain
Maryland	Mr. Manu Shah
Massachusetts	Mr. Richard F. Wilson
Michigan	Mr. Leo Arens
Minnesota	Mr. Dan Brannan
Missouri	Mr. John Schaefer
Nebraska	Mr. Randall D. Peters
Nevada	Mr. Michael Lawson
New York	Mr. David Woodin
North Dakota	Mr. Allan A. Coulin
Oklahoma	Mr. Red Miller
Oregon	Mr. Steve Reed
Rhode Island	Mr. Frank Corrao III
South Carolina	Mr. Don Turner
Texas	Mr. Darren McDaniel
Virginia	Mr. Curtis Meyers
Washington State	Mr. Ezekiel W. Lyen
West Virginia	Mr. Roger L. Russell
Wisconsin	Mr. John Corbin

Some of the respondents provided detailed answers to the survey questions, while others were relatively brief. This section presents their answers, summarizing all the various responses that were received, and in some cases highlighting interesting comments from individual respondents. The presentation follows the organization of the survey itself, and each survey question is discussed in turn.

It should be noted that the survey was not intended to be a statistically rigorous effort. Since it is not known why some states responded and others did not, the responses may be biased in some unknown way.[13] On the other hand, since responses were received from two-thirds of the states, with no part of the country particularly under- or over-sampled, the results can be considered a reasonable indication of conditions and practices in a substantial majority of the states. Nonetheless, the possibility of a bias should be kept in mind when examining and interpreting the survey results.

3.1.2.1 Answers to Questions in Part A: Speed Limit Change Data

A-1) Did your Department raise posted speed limits on any high-speed road sections following the repeal of the National Maximum Speed Limit (NSML) in 1995?

Among the states responding, only Oregon did not raise posted speed limits after the repeal of the NSML in 1995.

A-2) Has your Department studied the traffic impacts (for example, on speeds, highway safety, volumes and composition, route choice, etc.) of these speed limit changes?

A number of states carried out some form of study of the traffic impacts of the speed limit changes following the NMSL repeal. Studies considered changes in speeds, or crash statistics, or both. In some cases, the studies were carried out by state universities or research institutions commissioned by the DOT. Several states that carried out such traffic studies provided references to reports from those studies. In these cases, the project contacted the DOTs to obtain the reports. The reports obtained in this way are reviewed in Section 3.2 below.

A-3) Has your Department studied other impacts of the speed limit changes? Examples might include impacts on environmental factors (air quality and/or noise), business and commercial activities, or other areas.

A few of the reports identified in question A-2 discuss potential non-safety impacts of speed limit changes, but none mentions a specific study of these impacts. The review of these reports in Section 3.2 identifies these discussions.

A-4) Has your department studied the overall benefits and costs associated with the changes?

No such studies were mentioned.

3.1.2.2 Questions in Part B: Related Data

B-1) What traffic data (such as volume and composition, speeds, number of accidents and accident rates) does your Department collect and maintain on a regular basis?

All responding states carry out regular traffic monitoring activities including traffic volume and composition, and crash counts and rates. (The traffic count data might be the responsibility of a different section of the DOT than the crash data, however.) The collection of speed data is more variable between states, with some states collecting it routinely at certain locations; others collecting it at random locations on a spot basis; and yet others collecting it on the occasion of audits or assessments of individual roadways.

[13] We were however equally persistent with all non-respondents in our efforts to persuade them to participate.

B-2) Does your Department operate any instrumented highways (roadway facilities with a high density of traffic sensors and detectors collecting and recording data at short time intervals on an ongoing basis)?
California, Connecticut, Georgia, Illinois, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, New York, Rhode Island, Texas and Washington State reported operating instrumented highways that deploy a significantly greater density of data collection capabilities than is typical of a standard statewide traffic count program.

3.1.2.3 Questions in Part C: Speed Limit Enforcement Decisions

C-1) What role, if any, does your State DOT play in determining the levels and location of highway patrol deployments for speed limit enforcement on high-speed roads?
No state DOT reported having a direct role in determining speed enforcement activities: this is the responsibility of the State Police, Highway Patrol or similar agency. A number of state DOTs reported that they regularly provide police with data on crash locations and characteristics, and on speed limit compliance.

Several responses described specific arrangements that are of interest. The Washington State DOT meets regularly with the State Police to discuss issues of mutual concern, including speed limit enforcement. The West Virginia DOT makes recommendations to the State Police about locations meriting enhanced enforcement activities. In Missouri, the Division of Highway Safety has recently been transferred from the Department of Public Safety to the Department of Transportation. Among other functions, the Department of Highway Safety provides assistance to state and local law enforcement agencies for targeted enforcement. One of the anticipated benefits of the move to MoDOT is more efficient sharing of speed and crash data, which should improve the planning of enforcement activities.

Speed limit enforcement in work zones is a special case. A number of respondents described close coordination between their DOT and the police for the patrolling of work zones, including arrangements for compensating the police for this activity.

C-2) If the Department is involved in such decisions, how does it decide where and how intensively speed limits should be enforced?
In most cases, as noted above, the DOT's role consists at most of providing speed and crash data to support decisions made by the State Police or another similar agency. A few states provided additional details.

<u>New York:</u>
"State Police and NYSDOT are involved in an Aggressive Driving Campaign and NYSDOT has identified high accident locations where aggressive driving has led to a significant accident problem."

<u>Virginia:</u>
"VDOT coordinates with police for their presence to enforce work zone speed laws on larger projects involving comprehensive Congestion Management plan; VDOT also works with law

and public safety agencies to develop incident management components including speed enforcement."

Washington State:
"The WSP utilizes a number of statistical analyses from a variety of resources to make deployment and enforcement decisions. Collision data indicating the causation for collisions, speed, DUI, etc., are factors that drive these decisions. Enforcement practices are based on data driven decision making based on strict analysis of the WSDOT Speed Report for example."

West Virginia:
"In cooperation with the WV State Police, the DOT installs aerial enforcement markings at select locations on Interstate and other four lane highways. Our only other involvement is to recommend to the state police that they provide enhanced enforcement at certain locations identified as having a higher than average percentage of motorists violating the speed limit."

C-3) Were there changes in your State's enforcement policy following the repeal of the National Maximum Speed Limit in 1995?

Of the 33 respondents, 15 stated that there had been no change in enforcement policy. Ten respondents either indicated that they didn't know, or referred us to the State Police. Four respondents did not answer the question. Four respondents indicated that there had been a change in enforcement policy; their responses are reproduced below:

New York:
"Not sure, but initially State Police tried to prevent the unofficial tolerance level (about 7 to 8 MPH) from rising [after the NMSL repeal]. Speeds were already 10 to 15 mph above the 55 MPH speed limit and they did not want to see such a uniform shift occur when the speed limit became 65 MPH. So the enforcement tolerance initially became tighter, but as resources have become more difficult, the tolerance has loosened. I have had troopers tell me that you will get a 7 or 8 mph tolerance in a 65 MPH zone because judges want to see tickets that are non-disputable. Somebody could dispute that the radar or speedometer is off a few MPH, but if you are doing +15 MPH over the limit, then they got you."

North Dakota:
"Enforcement policy changed on four-lane divided highways."

Oklahoma:
"Only one change regarding speed limits occurred, which established a zero tolerance policy; and tickets for less than 9 miles over the speed limit were not recorded on the DMV record."

Washington State:
"Strict enforcement of the new 70 mph speed limit [following the NMSL repeal] was instituted. Media resources were solicited to provide the public with information on the change and the enforcement decisions."

C-4) What are the levels of traffic fine for different degrees of speeding? Are there other penalties as well (e.g. driver's license revocation)?

A number of states provided detailed descriptions of the system of speeding fines and penalties in place, or references to their on-line statutes. Many respondents suggested that the survey personnel contact the State Police or similar agency for information, or provided references to their on-line statutes. More detailed responses were received from several states.

C-5) What is the legal Blood Alcohol Content (BAC) in your State, and how and when has it changed in the last decade?
Most states reported that a BAC limit of 0.08% has been instituted relatively recently, although in a few cases the 0.08% limit has been in force for several years or more. A number of the states that still have a BAC limit of 0.10% in effect reported that the lower 0.08% limit is currently under consideration by the legislature.

C-6) Does your State have graduated driver's licenses and, if so, how and when did these arise? What sorts of restrictions on young drivers are in place?
Most respondents reported having graduated driver's licenses for young drivers and, in most cases, these were initiated in the past few years. (The respondent from Maryland pointed out that it was the first state to institute graduated licenses, in 1978.) A number of these respondents provided detailed information on the restrictions that are entailed; these typically involve limitations on driving after dark, on the number of passengers, and the like. Connecticut was alone in reporting no restrictions on young drivers. Other respondents referred us to the state police or similar agency.

C-7) Please suggest someone we might contact in another State agency (Department of Public Safety, State Police, etc.) for further information on speed limit enforcement decisions.
Most states recommended that the survey personnel contact the State Police or related agencies for further information on speed limit enforcement decisions. Responses usually provided information on specific contact persons in those agencies. Section 3.3 below presents the results obtained from a follow-on survey of State Police agencies.

3.1.2.4 Questions in Part D: Speed Limit Change Decisions

D-1) Please describe how speed limits are determined for high-speed roadways in your State. In determining speed limits, how much importance is given to design speeds versus observed uncongested operating speeds?
In general, most respondents reported that maximum speed limits on particular road classes are fixed by statute. Decisions about speed zones on particular road sections are generally based on engineering studies that may be initiated directly by the DOT, or at the request of local governments, police or (in some cases) citizens' or other groups. Such studies typically rely heavily on (i) the section's crash history, when safety is a particular issue in determining the speed; and (ii) observations of the 85th percentile operating speeds under free-flow conditions, in accordance with recommendations of the *Manual on Uniform Traffic Control Devices* (MUTCD) or its state equivalent(s). A number of other factors also may play important, but secondary, roles. On newly opened roads, the initial speed limit is generally determined using the design speed, but the limit may later be revised as operational experience is accumulated.

Arizona stated that a section's design speed did not affect its speed limit determination. Iowa explicitly mentioned design speed as a factor in determining speed limits, but emphasized that it is secondary to the observed speed. Massachusetts mentioned that a section's design speed was only used as an upper bound in setting its speed limit. Oregon stated that the design speed was used on new highways to determine a temporary speed limit, but that the permanent limit was based on observations of the 85^{th} percentile speed after the road had been in service for some time. California, Michigan, and Minnesota reported having datasets for comparing speed limits, design speeds, and operating speeds.

Some of the more detailed responses to this question are reproduced below:

<u>Illinois:</u>
"Maximum speed limits are statutory and determined by legislative action. Altered speed limits are set on the basis of an engineering and traffic investigation based principally on the 85th percentile speed with some adjustment factors such as the crash rate, access points, pedestrian activity and parking. Taken together, such adjustment factors may justify an altered speed limit up to 9 miles per hour less than the 85th percentile speed."

<u>Nevada:</u>
"Special traffic studies are conducted considering the criteria specified in the MUTCD. A recommendation is then made by the Traffic Information Division to the Chief Traffic Engineer who considers other criteria unique to the study area before forwarding his recommendation the Director, who makes a final determination based on the recommendations and his personal judgment. Design speed is viewed as the upper limit regardless of operating speeds, but operating speeds can suggest a lower limit than the design speed."

D-2) Please describe in detail the process by which your Department decides to modify (raise or lower) the posted speed limit on high-speed roads, either for individual road sections or for an entire class of facility (e.g. rural or urban interstates, other limited access facilities, other high-speed roadway).

The following comment is a typical response to this question:

<u>North Dakota:</u>
"Typically speed studies are conducted upon receiving a request to alter a speed zone. Based on the 85th percentile speed we try to set a realistic speed limit within 5 mph of this speed within legislative limits. Other considerations include horizontal or vertical alignment, crash rates/types, roadway design, access control, adjacent development and political."

Other factors that were cited as considerations in deciding about a possible speed limit change include crash history, sight distance, traffic volume, "field conditions", "engineering judgment" and the like. A number of states simply referred us to the MUCTD or their local equivalent for detailed information on the process used to make decisions about modifying speed limits.

D-3) Has the Department established any written rules or guidelines to be followed when making these decisions?

Arizona, California, Florida, Georgia, Idaho, Illinois, Kansas, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, New York, Oklahoma, Oregon, Texas, Virginia and West Virginia referred to specific written manuals, rules or policy guidelines for making decisions about changing the posted speed limits.

D-4) Please describe other factors (legal limitations, public opinion, interest groups, political considerations, etc.) that play a role in making decisions about raising speed limits.
A number of respondents described mechanisms in place in their states by which public opinions about speed limits can formally be expressed: for example, provisions by which citizen or other groups can request speed studies. Comments on the influence of political or other factors in speed limit decisions were few and generally rather circumspect. A sample of the responses is given below.

Arizona:
"While we try to minimize the above factors they do occasionally play a role."
California:
"Public opinion is a high priority when changing speeds on high speed facilities; California Vehicle Code section 22345.5, which stipulates that proposed speed limit changes must be coordinated with the California Highway Patrol and that county or city boards of supervisors may arrange public hearings to discuss proposed speed limit changes, ensures this. In addition, when the freeway speeds for cars and trucks were considered for changing after the repeal of the National Maximum Speed Limit, a committee was put together by the management of Caltrans to evaluate the proposed changes and to determine how best to proceed with the existing differential speed limit of 55 mph for heavy trucks. Committee membership included representatives of the Highway Patrol, trucking and insurance industries, local government and various safety interests who collectively made the decision to retain the differential speed limit on California freeways."

Iowa:
"The Iowa legislature has debated the speed limit issue every year since the repeal of the national maximum speed limit. So, yes legal limitations and political considerations are considered in the speed limit decision. In the past, we have also sought local/public opinion by informing the county/city officials of a planned increase in the speed limit for individual sections of road. In a couple of situations, the locals were opposed to the increase and it did not happen."

Minnesota:
"It would take 3 pages to answer these factors' individual impacts but it safe to assume that they do impact the decision making process based upon the intensity of each issue."

Missouri:
"According to state statute, [the DOT's] study is the only deciding factor in raising/lowering speed limits. We may consider requests to change speed limits."

Nevada:

"All of the above [i.e. legal limitations, public opinion, interest groups, political considerations, etc.] factor into the Director's final decision, but are not considered as part of the special studies that are conducted."

3.1.2.5 Comments From Part E: General Comments

E-1) We welcome any observations that you may have about the impacts of speed limit changes on high-speed roads in your State. As an example, you might have comments on the following questions:

- *Overall, has the repeal of the NMSL affected traffic safety in your State?*
- *Have speed limit changes on high-speed roads influenced driver behavior and/or traffic safety on other road classes as well?*
- *Have truck route choices changed since the NMSL repeal? Are some portions of your State's roadway network either safer or less safe because of this?*
- *Has the elimination of NMSL-related speed enforcement mandates changed the focus of highway patrol activities? Has this had an effect on traffic safety?*
- *Have changes in speed limits on high-speed roads impacted the environment? the business community? public opinion? other impacts?*
- *Any other issues that you would like to raise?*

This question elicited useful and interesting comments from a number of respondents. There were several brief anecdotal comments to the effect that the NMSL repeal either (i) had no effect on traffic safety, or (ii) had an initial negative effect that became negligible after a few years as drivers adjusted to the changed speed situation.

Some of the more illuminating responses that were received are reproduced below. In an attempt to ensure candid responses, the instructions for this question in the survey promised that comments on this question would remain anonymous. Accordingly, any readily-identifying information that was included in the replies has been redacted.

<u>Respondent 1:</u>
Overall, has the repeal of the NMSL affected traffic safety in your State?

"I will provide this summary that I had prepared back in 1998. On December 18, 1995 the speed limit was raised from 55 mph to 65 mph on approximately 2,500 miles of freeways. On January 8, 1996 the maximum speed limit on nearly 1,300 miles of rural freeways was increased from 65 mph to 70 mph.

Safety:
"The fatal accident rate (accidents/MVM), for all freeways where the speed limit was changed, increased by about 4.4%. This change is based on accident data for two years before and two years after the speed limit change.

"The fatal plus injury accident rate (accidents/MVM), for all freeways where the speed limit was changed, increased by about 2.3%. This change is also based on accident data for two years before and two years after the speed limit change.

"The fatal accident rate for all freeways statewide (includes freeways not having a speed limit change) increased by 1.5%. There was no significant change in the fatal plus injury accident rate for all freeways statewide. These results are based on a comparison of accident data for 1994-1995 with accident data for 1996-1997.

"The percentage of total accidents where speed was the primary cause increased slightly from 44.8% before the speed limit change to 44.9% after the speed limit change. These percentages are based on accident data for a representative sample of locations where the speed limit was changed and on similar 18-month before and after periods. In comparison, the 1997 statewide percentage of total accidents related to speeding was approximately 42.6%.

"The percentage of total accidents where the influence of alcohol was the primary cause decreased from 6.4% before the speed limit change to 5.5% after the speed limit change. These percentages are also based on accident data for a representative sample of locations where the speed limit was changed and on similar 18-month before and after periods. In comparison, the 1997 statewide percentage of total accidents involving the influence of alcohol was approximately 6.1%.

Operations:

"The average 85th percentile speed of vehicles within the 65-mph zones changed from 67.1 mph before to 68.8 mph after the speed limit increase, a 1.7-mph or 2.5% increase.

"The average 85th percentile speed of vehicles within the 70-mph zones changed from 70.3 mph to 72.3 mph after the speed limit increase, a 2.0-mph or 2.8% increase.

Conclusions:

"The average 85th percentile speeds have increased a very small amount (1.7 mph and 2.0 mph) since the initiation of the new higher speed limits on [our] freeways.

"Safety data indicates a 4.4% increase in the fatal accident rate and a 2.3% increase in the fatal plus injury accident rate for all freeways having a speed limit change. These changes are not significant, considering that the accident rates for the after period are both lower than the 1996-1997 statewide accident rates for all freeways (6.0% lower for the fatal accident rate and 16.5% lower for the fatal plus injury accident rate).

"The percentages of total accidents, where speed and the influence of alcohol were the primary causes, did not change significantly after the speed limit increase. The percentages of these types of accidents were approximately the same as the statewide percentages for 1997.

"Subsequently reports prepared by [a state] university which evaluated the before and after impact of the change in speed limits using a predictive model determined that collision rates did not decline as rapidly on freeways where the speed limit had been increased as those where the speed limit was retained at 55."

Have speed limit changes on high-speed roads influenced driver behavior and/or traffic safety on other road classes as well?

"Unknown."

Have truck route choices changed since the NMSL repeal?
"Unknown."

Respondent 2:
"When the NMSL was repealed, the […] Department of Transportation, along with the […] State Police, organized a task force to study the impact of the abolishment of the national maximum speed limits. This study included engineering traffic investigations, as required by state law. These investigations used data from automatic speed monitoring stations which were then in place throughout the state and applied widely accepted speed limit determination methodologies. The study justified retention of the 55-mile-per-hour speed limit for the conventional state and local two-lane highway system and the 65-mile-per-hour speed limit for the rural freeway system. This decision was supported by the […] General Assembly […]. This act established statutory maximum speed limits of 55 miles per hour on both the state and local highway systems and a maximum speed limit of 65 miles per hour on both the rural freeway and tollway system.

"The task force did, however, recommend increasing the speed limit to 65 miles per hour on some rural, four-lane divided, high-type highways and on some portions of rural freeways which fell under the federal guideline for urban areas, but which operate as rural highways. A review of the accident rates on these systems showed that the speeds could safely be increased with little, if any, impact on either the number or severity of accidents.

"Altogether, the speed limit was raised on less than 250 miles of highway (less than one percent by mileage). This included 126 miles of Interstate and other freeways and 118 miles of 4-lane divided, high-type highways.

"We have no evidence that the speed limit changes on high-speed roads influenced driver behavior and/or traffic safety on other road classes or roads, no evidence that truck route choices changed, and no evidence of any effect on traffic safety or the environment."

Respondent 3:
"Drivers' average speeds have slowly been increasing."

Respondent 4:
"The traffic safety in [our state] has been affected by the repeal of the NMSL. There is continued pressure to increase the speed limit and our experience on those sections that have had increases has indicated an increase in the severity and numbers of crashes. Even if the increased speed limits do not lead to additional crashes, those crashes that do occur will be more severe.

"We continue to see slight increases in speeds on our two lane highways and our interstate highways. I don't know if that is related to the higher speed limits in other states or more a reflection of today's society.

"With increasing speed limits, there are a couple other issues that surface and should be addressed. Should trucks be allowed to drive the faster speeds? This inevitably comes up during legislative debates, should there be a separate lower truck speed limit. Past research is limited and the results vary. The other issue is the minimum speed limit. We currently on have a minimum speed limit of 40 mph on the Interstate system. It was 40 mph when the maximum was 55 mph. Now the maximum is 65 mph and the minimum has not changed. If the maximum is increased again, should the minimum speed limit be increase to try and keep the variance in speeds at a minimum level?"

<u>Respondent 5:</u>
"…As I recall crashes either stayed the same or were reduced on 93 percent of our highways when we raised the speed limit."

<u>Respondent 6:</u>
"We've experienced a slight increase in speeds."

<u>Respondent 7:</u>
"We have no unique data to quantify any of these issues."

<u>Respondent 8:</u>
"The NMSL never was about safety, it was about energy conservation. Pick whatever study you like and unscientific people will distort the results to fit their argument. I believe any legislatively mandated speed limit is inappropriate. Different roadways have different 'characteristics' and those, along with prevailing speeds, should determine the appropriate limits.

"The repeal of legislatively mandated limits was a good thing and a long time coming. States have the responsibility for all matters concerning their roadways and ought to have the authority to manage them as they see fit. The NMSL was yet one more example of creeping Federalism, as is the .08 BAC, federally mandated seat belt laws, federally mandated revocation of drivers licenses for any drug related offense, the LCV size and weight freeze, and on and on. The elimination of any and all of them is in keeping with the fundamental principals of the Constitution as articulated in the 10th amendment which is that 'The powers not delegated to the United States by the Constitution, nor prohibited by it to the States, are reserved to the States respectively, or to the people.' Amen to that."

<u>Respondent 9:</u>

"1. Repeal has had minimal effect on traffic safety: On highways with 65 MPH all accident rates are down, number of fatalities are down, but total number of accidents and injuries are up.

"2. Yes, speeds are up on other highways as well.

"3. Trucks probably are sticking more to the interstates with 65 MPH as it allows them to get to their destinations faster and with less fear of a ticket.

"4. Not sure - Need to ask State Police.

"5. People seemed to be satisfied with the 65 MPH speed limit based on the volume and type of letters we receive on the subject. Most letters now ask why can't you add highway XX, rather than I wish you did not increase the speed limit to 65 MPH."

<u>Respondent 10:</u>
"The elimination of NMSL related speed enforcement mandates, have not been appreciable.

"Public opinion seems to be favorable towards the increase in speed limits in [our state].

"Some truck traffic may have changed to include roadways with higher speed limits. The Patrol does not have data to substantiate this.

"Traffic fatalities have not risen in [our state] since the speed limit increases in 1996. In some years after 1996, traffic fatalities were substantially lower."

<u>Respondent 11:</u>
"[Our] drivers tend to drive up to 10 miles per hour over any posted speed limit. Raising the speed limit to the 85% usually results in motorist driving faster than the 85% speed. The key to maintaining safe speeds on our roads is enforcement and there is very little enforcement of motorists speeding up to 10 miles per hour over speed limit."

<u>Respondent 12:</u>
"[Our] maximum speed limits are legislated. The lower speed limits are determined by the 85th percentile speed. Environmental Speed Limits have been enacted in [three cities]. The lower speeds did not have much of an impact on the 85th percentile speeds."

<u>Respondent 13:</u>
"Since the repeal of NSML in 1995, most states have changed speed limits on their interstate highway systems in our nation. Due to there not being any policy, procedure or standard, the state agencies made their decisions on their own. This situation has brought lots of controversies or concerns regarding the effects of such changes on safety, operation, roadway design,

enforcement, environment and productivity, etc. In addition, no reliable research reports have been found.

"Therefore, it is strongly recommended that NCHRP prepare a guideline for the changes of speed limits based on engineering and statistical data analysis."

Respondent 14:
"When we raised speed limits, we set them to reflect the actual operating speeds on the affected roadways. We have not identified any significant impacts on route choices, safety or other issues."

3.1.3 Conclusions From the Survey of State DOTs

The results of the survey of state DOTs provided the study team with a considerable amount of useful information. Although the survey was not exhaustive, many of the responses shed light on hypotheses about speed limit change impacts that were of interest to the study. This section highlights a number of the most relevant and interesting conclusions that were drawn from survey results.

3.1.3.1 Studies of the Traffic Impacts of the NMSL Repeal

In general comments, respondents felt that average travel speeds had increased following the repeal, but most noted that this was part of a general trend established over a long time period and affecting most road classes.

With one exception, survey respondents intuitively felt that impacts of the NMSL repeal on traffic safety had been either insignificant or non-existent. One respondent did cite an increase in crash numbers on sections with raised speed limits, but did not provide data to quantify the effect. The same respondent noted that higher speeds could be expected to increase the severity of the crashes that do occur.

3.1.3.2 Studies of the Non-traffic Impacts of the NMSL Repeal

No state that responded to the survey has studied the non-traffic impacts of the NMSL repeal, with one partial exception: the NYSDOT study of post-NMSL impacts did consider effects on the trucking industry.

3.1.3.3 Impacts of the NMSL Repeal on Traffic Enforcement

State DOTs that responded to the survey reported that they have no direct responsibility for decisions about traffic enforcement; their role is generally limited to providing the State Police or similar agency with data on locations with high crash rates or speeds.

The respondents made very few references to systematic changes in enforcement policies post-NMSL. A number of states stated that they became less tolerant of speeding than they had been during the period of the NMSL. No information obtained so far supports the hypothesis of a systematic shift away from speed enforcement on high-speed roads to other types of policing activity following the repeal. Interestingly, Washington State specifically noted that a policy of strict speed enforcement was implemented specifically on roads with limits that were raised to 70 mi/h.

3.1.3.4 Systemwide Impacts of the NMSL Repeal

The project Scope of Work asks for an analysis of the "systemwide effects" of speed limit changes, mentioning trip generation and diversion as specific examples.

None of the respondents referred to trip generation impacts in any way. Two respondents speculated that some truckers might have shifted to Interstates with higher speed limits following the repeal, in order to save travel time and reduce their exposure to police patrols. Other respondents simply replied that no data was available to investigate this potential effect.

Some researchers have speculated that speed limit changes on high-speed roads could have "spillover" effects on other road classes as, for example, drivers change their tripmaking (particularly route choice) decisions or police change their speed enforcement strategies. Two respondents explicitly mentioned that there was no evidence to support such a hypothesis, while the others did not refer to the idea. It seems likely that such effects, if present at all, are small and difficult to detect.

3.1.3.5 The Speed Limit Change Decision Process

Little information was received concerning decisions that affect the maximum speed limit for entire classes of roadway facilities; the responses tended to focus much more on decisions affecting individual facilities or roadway sections.

The practical details of the speed limit change decision process vary somewhat from state to state, but all responding states rely on observed 85th percentile free flow speeds as one of the principal factors used in setting speed limits, with consideration also given to any of a number of secondary factors. The FHWA's *Manual on Uniform Traffic Control Devices* (MUTCD) is the standard engineering reference used in setting speed limits, although a number of states have developed local adaptations of the MUTCD and/or speed limit policy guidelines.

Most states reported that a roadway section's design speed was not considered when setting speed limits, although a few respondents mentioned using design speed as a secondary factor, or as the basis for setting the initial speed limit on a newly opened road.

NCHRP project 15-18 focused on relationships between design speeds, operating speeds and speed limit decisions. The final report of the project (Fitzpatrick et al. 2002) may be consulted for further information on this topic.

3.1.3.6 Other Insights from the Survey

One respondent mentioned the question of different speed limits for trucks as an issue worth considering.

The same respondent suggested that the impact of changes to *minimum* speed limits should also be studied. When the NMSL was in effect, the national minimum and maximum speeds on Interstates were 40 mi/h and 55 mi/h, respectively. With the NMSL repeal, many Interstates have maximum speed limits of 70 mi/h or more, while the minimum speed has generally remained at 40 mi/h. Has this increase in the range of legal speeds produced traffic or other impacts? The literature appears to be silent on this question.

Other respondents emphasized the importance of speed limit enforcement and enforcement policies in determining actual speeds. One suggested that drivers use a posted speed limit as a reference and then choose to drive at a somewhat higher speed; strict enforcement is needed to ensure that the limit is actually respected.

3.2 Review of State Studies of the NMSL Repeal

Question A-2 of the survey of state DOTs identified studies of the NMSL repeal that had been conducted by the Departments. The project obtained and reviewed these studies. The following subsections present and discuss the reports so obtained.

3.2.1 Arkansas

In Arkansas, the State Highway Commission is responsible for establishing speed limits. Following the NMSL repeal, the Commission met in July and August 1996 to consider increasing speed limits on freeways with rural and suburban characteristics, and on rural expressways with high-type partial access control. The recommended new speed limits were as follows:

Rural freeways:	cars: 70 mi/h; trucks: 65 mi/h
Suburban freeways:	65 mi/h
Urban freeways:	60 mi/h
Rural expressways:	65 mi/h, except where review indicates need for a lower limit

These recommendations were based on a *Speed Limit Study for Arkansas Highways* (1996) prepared earlier by the Arkansas State Highway and Transportation Department. In addition to its recommendations, this study noted briefly the increased mobility, efficiency, time savings and cost savings that might derive from increased speed limits.

Following implementation of some of the recommended speed limit changes, a *Study of the Safety Impacts of Increased Speed Limits in Arkansas and a Review of Proposed Speed Limit Increases on Additional Routes* (November 1997) carried out a simple before-after comparison of fatal crash counts and fatalities one year before and after post-NMSL speed limit increases. Possible changes in traffic volumes and other safety-related factors were not controlled for. The study found a 5% increase in fatal crashes and a 15% increase in fatalities on all routes with raised limits. The changes varied considerably by facility type. Fatal crashes and fatalities decreased by 12% and 10% respectively on rural freeways, but increased by 89% and 145% on suburban freeways.

In 1998, the State Highway and Transportation Department completed a follow-up study, *Speed Limit Study for Arkansas Highways – 1998 Update*. This study built on the fatal crash and fatality data developed by the 1997 study for different roadway classes following the changes suggested in 1996. It generally recommended full implementation of the post-NMSL limits, consistent with safety and speed data. It noted that the recommended limits would provide a smooth transition between speed limits on urban, suburban and rural freeways. In the particular case of rural expressways, it recognized their variability regarding degree of access control and connectivity to other similar facilities, and recommended lower speed limits for specific highways.

3.2.2 Iowa

The 1995 NMSL repeal led to the preparation of a *Report on Speed Limits and Safety for Iowa Highways*, published by the Iowa Task Force on Speed Limits in January 1996. The report contained a thorough and thoughtful review of possible approaches to post-NMSL speed zoning policy in the light of Iowa and national speed and traffic safety trends. However, it did not make specific recommendations regarding speed limits, preferring to compile, analyze and present the relevant facts, and leaving speed limit policy decisions to the State Legislature and other policy makers.

In 1996, the Legislature authorized the Iowa DOT to increase speed limits to 65 mi/h on certain divided, multi-lane highways. Following an initial review, 248 miles of highway had their speed limits so increased. By January 2001, a total of 680 miles on 28 sections of Iowa's rural freeways and expressways had had their limits increased to 65 mi/h following a review of section design characteristics and crash history, and a field inspection.

The Task Force on Speed Limits published in January 1997 a *Report on Results of Speed Limit Changes After Repeal of the National Maximum Speed Limit*. Subsequently, it has published annual update reports on speed limits; the latest available report is for 2002. These annual update reports track a number of speed, travel, safety and enforcement variables. They also contain comparisons of Iowa's highway safety experience with that of neighboring states.

The reports examine trends in the percentile distribution of speeds. They document a steady upward trend in 85th percentile operating speeds in the years following the implementation of the new speed limits. They also note an irregular downward trend in the *pace speed* (the 10 mi/h speed range containing the highest number of vehicles), which suggests increasing speed variance. However, it is possible that this trend reflects the effects of increasing congestion (which tends to accentuate the differences between peak and off-peak travel conditions) more than those of the speed limit change (which may or may not increase the variability of individual vehicle speeds). The reports also highlight a roughly upward trend in the percentage of vehicles exceeding the 65 mi/h speed limit. However, a much larger fraction of Iowa drivers complies with the 65 mi/h limit than did with the 55 mi/h limit during the NMSL period.

With respect to rural expressways and freeways for which the speed limit was increased, crash rates were found to increase between mid-1996 and the end of 1997. These increases were found across all considered crash categories, including fatal crashes, fatal and injury crashes, all crashes, fatalities, fatalities and major injuries, and other (less severe) injuries. All crash rate categories increased by at least 20%, with fatal crashes and fatalities increasing by 497% and 587% respectively. Crash rates on non-interstate freeways with full access control were roughly two to three times higher than rates on the Interstate system.

The number of speeding citations issued by the State Patrol did not change significantly in the period 1993-1999; however, the number decreased in 2000 and 2001.

3.2.3 Kansas

Speed limit statutes in Kansas were changed in March 1996, following the NMSL repeal. The revised statues authorized limits of 70 mi/h (up from 65 mi/h) on most rural multi-lane divided highways, and of 65 mi/h (up from a variety of lower limits) on most urban interstate and two-lane rural highways. By June 1996, new speed limit signs had been posted on most highways in the state.

A study conducted for the Kansas Department of Transportation (KDOT) by researchers at Kansas State University (Najjar *et al.* 2000) investigated possible changes in speeds and crash rates as a result of the speed limit changes, applying before-after analysis methods to both rural interstate and rural two-lane highways.

The speed analysis concentrated on the 85th percentile speed, using t-tests to compare section speeds in the approximately one-year periods before and after the speed limit change. On rural interstates, the research found (at a 95% confidence level) that the 85th percentile speed increased by 3 mi/h following a 5 mi/h speed limit increase.

The safety analysis distinguished rural interstates, urban interstates and two-lane rural highways, and considered total crash rate, fatal crash rate and fatality rates using a crash database maintained by the KDOT Bureau of Transportation Planning. Investigation of possible rate changes was conducted using a three-step sequential analysis methodology consisting of:

- a statistical (t-test) comparison of monthly crash rates of each type in the periods 1993-1995 *vs.* 1997-1998 (the year 1996, in which the speed limit changes took effect, was intentionally omitted);
- an examination of time series plots of crash rates in the period 1993-1998, to determine if any significant change in rates could be visually detected; and
- a final determination, considered conclusive if the preceding two steps agreed regarding the presence or absence of a significant change, and inconclusive otherwise.

This methodology determined that there was no significant change in the three considered crash rates on either rural or urban interstates following the speed limit change. On the other hand, the changes in these rates on two-lane rural highways were found to be significant. These latter represent a group with heterogeneous engineering and traffic characteristics, and saw post-NMSL speed limit increases ranging from 5 to 20 mi/h. Closer examination of the results revealed that about 7% of the rural two-lane highway sections accounted for most of the observed increase in crash and fatal crash rates.

3.2.4 Louisiana

In Louisiana the speed limit on rural interstates was raised from 65 to 70 mi/h on August 15, 1997; limits on urban interstates remained unchanged. Schneider (undated) carried out an analysis of the impact of the speed limit change on the number and severity distribution of crashes, distinguishing between fatalities, injuries and PDO crashes.

A comparison of roadway crash performance in 1996 and 1998 identified a 37% increase in fatal crash counts on interstates, albeit with no overall increase in fatal crashes when all roadways were considered. Comparing the same two years, there was a 9% decrease in injury crashes across all roadways, but a 1% increase on interstates; similarly, there was a 2% increase in PDO crashes on all roadways, but a 14% increase on interstates.

Louisiana has specific safety issues that most other states do not have. The presence of swamps in much of southern Louisiana results in significant numbers of elevated bridges and highways. These are particularly prone to crashes because of the limited maneuvering room and the prevalence of fog due to the nearby water. The analysis found considerably greater increases in all crash rates on elevated interstate facilities compared to other interstate facilities.

The report did not examine VMT and crash rates, but is noteworthy for considering a variety of other safety-related factors including, among other things, the age and gender distribution of drivers and their crash involvement, the distribution of crashes by day of week and time of day, the use of seatbelts and the effects of weather conditions.

The study also attempted to ascertain the change in fuel consumption costs associated with the speed limit change. Changes in VMT and taxed fuel consumption were very small between 1996 and 1998. The report notes an overall decrease of 0.2% in fuel economy (mi/gallon) during this period, but notes that the changing vehicle fleet (increased numbers of SUVs and light trucks) makes it impossible to impute this change to the speed limit change.

Considering the effect of speed limit change on travel time costs, the study notes that approximately 85% of travel in Louisiana occurs on urban interstates and roads with speed limits of 55 mi/h or less. About 25% of VMT is produced on interstates, of which 60% (i.e. 15% of total VMT) occurs in rural areas where the speed limit was increased. The report concludes that the change in travel time and associated costs would be most strongly felt by long distance travel, such as commercial trucking and vacation travel.

3.2.5 Michigan

Following the NMSL repeal, the Michigan Legislature directed the Michigan Department of Transportation (MDOT) and the Michigan State Police (MSP) to designate 500 miles of rural freeway for which the speed limit would be increased from 65 to 70 mi/h, and to study the impact of the speed limit change on vehicle speeds and crashes over a six-month period.

Taylor and Maleck (1996) carried out this study. They found increases in the 50th and 85th percentile speeds of less than 2 mi/h at some locations, with most locations exhibiting increases of less than 1 mi/h. The lags inherent in reporting crash data did not allow an analysis of the crash impacts of the speed limit change.

The legislature then authorized the MDOT to raise the speed limit on an additional 1000 miles of rural freeway on January 1, 1997. (Truck speeds remained at 55 mi/h during this time.) The study of the speed limit change impacts was expanded to include the additional freeway sections. Following a series of reports on the shorter-term impacts of the changes, Taylor (2000) issued a comprehensive study of the speed limit change impacts over the period 1997-1999, comparing traffic and crash data for this period with those for the three-year period preceding the speed limit change.

It was found that, over the considered period, total crash counts increased by 10.5%, severe crash counts increased by 4.5%, but fatal crash counts decreased by 9.3% on the freeways experiencing the speed limit changes. Lack of comprehensive traffic volume data made it impossible to compute crash rates and identify rate changes. However, a comparison of the increase in total crash counts with the estimated growth in VMT during the same period suggested that the total number of crashes increased by less than the overall traffic growth rate.

3.2.6 New Jersey

The 1987 NMSL relaxation had little effect in New Jersey because it concerned only rural interstates, of which New Jersey has very little mileage. The 1995 NMSL repeal, on the other hand, led the New Jersey Legislature in late 1997 to raise the 55 mi/h speed limit to 65 mi/h on portions of the highway network including interstates and other highways with similar design and access control. A default limit of 65 mi/h was also established for the New Jersey Turnpike, the Garden State Parkway and the Atlantic City Expressway.

It was decided that limits would be raised on approximately 400 miles of highway, and that these would be monitored over an 18-month period to determine the impacts of the speed limit change, in order to develop a policy regarding speed limit changes on other portions of the highway network. Impacts monitored during the 18-month period were to include travel speeds, safety performance, enforcement experience and environmental impacts (air quality and noise).

Approximately 475 miles of roadway were selected for this purpose in May, 1998. A number of criteria were applied in the selection process, including minimum section length (10 miles), minimum design speed (65 mi/h), adequate spacing of access ramps, and absence of significant recurring congestion (to avoid creating unsafe driving situations by the speed limit increase). The application of these criteria had the effect of concentrating the selected segments in rural and suburban environments.

In advance of the speed limit change implementation, a more aggressive traffic fines schedule for violations of the 65 mi/h limit was developed and put in place. "Before" traffic volume and speed measurements were also carried out on and near all the highway sections designated for changed limits, as well as on a sample of highways for which the speed limit would not change.

NJDOT measured all sections' traffic volumes and speeds at least once every three months during the 18-month period. Throughout the period, the State Police collected data on crashes and traffic law violations.

Average speeds were found to change by minimal amounts on the sections with changed speed limits. Typical changes were less than ±2 mi/h. The only exception was on the New Jersey Turnpike, for which average speed increases of 3-4 mi/h were found. It was noted that other factors, such as enforcement policy changes and public outreach efforts, probably affected the observed speed changes.

Air quality and environmental noise level changes were determined using standard models based on measured traffic volumes and travel speeds, and taking account of possible travel pattern (routing) responses to the speed limit change. It was determined that the speed limit change resulted in increases of 0.20%, 0.90% and 1.15% in traffic-related emissions of volatile organic compounds (VOCs), nitrous oxides (NOx) and carbon monoxide (CO), respectively. These changes were deemed nominal. Similarly, it was determined that the noise level change resulting from the observed (small) travel speed changes would not be perceptible in the noise environment adjacent to the highways.

Fatal crashes and fatalities decreased on the concerned sections by 7.9% and 9.6%, respectively, in the 18 months following the speed limit change compared to a similar period before the change. Total crashes increased by 18.3% on these sections, while the number of crashes with injuries and number of injuries increased by 9.4% and 5.9%, respectively. It was found that 55 mi/h zones adjacent to the 65 mi/h zones exhibited slightly greater increases in total crash counts. The study noted that, in the period between 1984 and 1996, crash rates on New Jersey highways varied by up to 12% per year. Consequently, in the 18-month duration of the impact study, it was not possible to determine conclusively whether the observed changes were due to normal fluctuations in traffic rates, or were an effect of the speed limit changes themselves.

3.2.7 New Mexico

Following the NMSL repeal, the New Mexico Legislature set the maximum permissible state speed limit at 75 mi/h, effective May 15, 1996. Beginning on that date, the New Mexico State Highway and Transportation Department began posting new 75 mi/h speed limits on many rural highways formerly having 65 mi/h limits. The specific highways had been identified in engineering studies conducted earlier, and included the state's three rural interstates. Criteria considered in these studies included design speed, pavement condition, level of traffic congestion, and existing travel speeds. In conjunction with the speed limit changes, New Mexico put in place an ongoing effort to study the effects of the higher speed limits through the analysis of speed monitoring and traffic crash data.

Davis (1998) provides an analysis of speed monitoring data collected several months before and after the implementation of the speed limit change, and of crash data over a period from two years before to one year after the speed limit change.

It was found that, on two of the state's rural interstates, average and 85th percentile speeds increased by over 2 mi/h, and the percentage of vehicles exceeding 80 mi/h almost doubled. Speed increases on the remaining rural interstate were less than 1 mi/h, and the percentage of vehicles traveling over 80 mi/h increased very slightly. This facility carries a significant fraction of heavy vehicle traffic, which may account for some of the difference.

On the two rural interstates where travel speeds increased, towaway crashes increased by 29%, injury counts by 31%, incapacitating injury counts by 44% and fatalities by 50%. On the interstate with much smaller speed increases, there was a small but statistically insignificant decrease in crash severity. The increases in crash and injury counts were much larger than the increase in traffic volumes on the same facilities during the study period, so that the crash and injury rates increased significantly.

The increase in incapacitating injuries affected out-of-state drivers much more than New Mexico drivers, suggesting that increased vacation travel may be responsible for the increase in injuries. Injury occurrence tends to peak during the summer travel season, corroborating the hypothesis. Observed seat belt usage rates by New Mexico drivers are among the highest in the nation, and the difference in seat belt usage may account for some of the difference in the injury increase between New Mexico and out-of-state residents.

On the two most affected rural interstates, multiple vehicle crashes accounted for 63% of the increase in incapacitating injuries and, of these, 84% occurred between vehicles traveling in the same direction (primarily through side swipes and rear-end collisions). This suggests that speed variance may have become a problem on these facilities following the speed limit increase.

Many sections of New Mexico's rural National Highway System experienced speed limit increases (typically to 65 mi/h, although some were posted at 60 mi/h and a few remained at 55 mi/h). Taken as a whole, this network is very heterogeneous, and there was no apparent overall effect of the speed limit changes on either speeds or crash performance at the level of this system.

3.2.8 New York

In June 1995, legislation was approved in New York State to allow for a 65 mi/h speed limit on approximately 1,200 miles of rural interstates and other highways with similar design and usage characteristics. Since New York State had chosen to not change speed limits at the time of the 1987 NMSL relaxation, limits on these facilities had remained at 55 mi/h and the speed limit increase was uniformly 10 mi/h.

At the time of the speed limit changes, the New York State Police, with authority for speed enforcement on the affected facilities, undertook a number of measures to enhance compliance with the new limits. These included dissemination of public service announcements and informational literature on speeding consequences, establishment of dedicated highway patrols and speed enforcement details, and increases in the amount of speed enforcement equipment available to patrolling vehicles.

The legislation also required the New York State Department of Transportation (NYSDOT), in conjunction with the New York State Thruway Authority (NYSTA) to prepare and submit a report on the impacts of the speed limit increases. Impacts on crash performance, travel speeds, traffic volumes, traffic mix (commercial vehicle percentage), speed limit compliance, as well as on the trucking industry and general public were specifically to be identified. In 1999, NYSDOT and NYSTA, together with the State Police and Department of Motor Vehicles, published their *Report on the 65 MPH Speed Limit in New York State*.

The impact of the speed limit changes on crash counts and rates was performed using a before-after analysis covering three years before and three years after the speed limit change. It was found that total, fatal and injury crash rates decreased by 4%, 29% and 5%, respectively, on the roads with increased limits.

In the period just prior to the speed limit change through December 1998, it was found that average travel speeds on affected NYSDOT facilities increased from 64 to 67 mi/h. (Systematic "before" speed data was not available for NYSTA facilities.) The 85th percentile speed increased from 69 to 74 mi/h, and the percentage of traffic exceeding the speed limit by more than 10 mi/h dropped from 40% to 11%.

Between 1994 and 1998, traffic volumes on affected NYSDOT facilities increased by 13% on average. On these facilities there was an average increase of 8% in the percentage of commercial vehicles, although the specific composition varied considerably between facilities. Statewide, the VMT on rural interstates increased by approximately 11% over the same period. Total volumes on affected NYSTA facilities increased by 6%-21% over this period, with major road sections typically seeing much smaller increases in the percentage of commercial vehicles. The report notes that NYSTA volumes might have been affected by independent factors such as the inauguration of the E-Z pass system.

The number of speeding tickets issued by the State Police decreased by 0.4% between the three year "before" and the three year "after " periods. Ticketing records suggest the presence of "speed creep" (a tendency for ticketed speeds to increase over time following a speed limit change) of 0.6-0.9 mi/h/year, but the report notes that the observation period is too short to draw definitive conclusions regarding such trends.

As part of the report preparation, discussions were held with the New York State Motor Truck Association (NYSMTA) regarding the specific impacts of the speed limit changes on truckers and the trucking industry generally. The NYSMTA did not have an official position regarding the 65 mi/h speed limit, and it was not aware of any studies of the speed limit change impacts on the trucking industry. However, the Association reported that the general consensus of its members was that increasing the speed limit to 65 mi/h in New York State had little impact on the trucking industry. The Association favors a single speed limit for all vehicles, rather than differential limits as practiced by some states.

Finally, the report estimated that roughly 4.4 million vehicle-hours per year were saved in New York State as a result of the increased limits. This figure was developed using average speed data and traffic volumes on the affected facilities.

3.2.9 Texas

With the repeal of the NMSL, the Texas speed limit law of 1963 went back into effect for the first time since 1974. This law requires the Texas Department of Transportation (TxDOT) to post passenger vehicle daytime speed limits of 70 mi/h and nighttime limits of 65 mi/h on all state roadways outside urban areas, unless engineering and traffic studies demonstrate that lower speed limits are warranted. Truck speed limits on these facilities are set at 60 mi/h during the daytime and 55 mi/h at night. TxDOT conducted studies of the state highway system to identify sections that should have speed limits lower than the maximum allowed. Except where the need for such reduced limits was identified, speed limits were generally increased from 65 to 70 mi/h on rural interstates, and from 55 to 70 mi/h on other facilities affected by the NMSL repeal (urban interstates, rural multi-lane divided highways, urban multi-lane divided highways, rural multi-lane undivided highways, and rural two-lane US and state highways).

Speed limit change impact studies were also conducted. An initial study by Pezoldt *et al.* (1997) reported on impacts of the speed limit changes after nine months of operational experience, focusing on rural and urban interstates. A later study by Griffin *et al.* (1998) extended the analysis to include data through early 1997, and to encompass non-interstate as well as interstate facility types.

The 1998 study carried out three main types of analysis: a comparison of measured vehicle speeds in the periods before and after the speed limit change, a longitudinal analysis of injury (i.e. non-PDO) crashes, and an analysis of confounding factors that may have affected highway safety performance during the same period as the speed limit changes.

Speed measurements were available from 30 permanent speed monitoring sites on highways for which the speed limits were raised to 70 mi/h in 1996, and generally covered the period from 1991 through 1997. These do not necessarily constitute a statistically representative sample of speeds on all highways with raised limits (for example, urban facilities are very under-represented), but can serve to indicate the nature of any speed changes that may have occurred. Moreover, the monitoring equipment provides 24-hour averages over all vehicles, and so does not distinguish daytime/nighttime or car/truck speeds. It was found that, following the speed limit change, average speeds on the rural interstates in the speed monitoring sample rose by roughly 3 mi/h, and by 8, 4, 7 and 5 mi/h, respectively, on the urban interstates, rural US highways, urban US highways, and rural state highways in the sample.

Crash data used in the analysis were derived from the Texas Department of Public Safety Accident Files. Crashes are classified as K, A, B or C according to the most severe injury sustained: fatality, incapacitating injury, non-incapacitating injury or possible injury, respectively. Aggregate crash classes were constructed by combining the above classes: K (fatal crash); KA (crash with fatal or incapacitating injury); KAB (crash with fatal, incapacitating or non-incapacitating injury); and KABC (crash with any kind of injury). PDO crashes were not considered in the analysis. Twenty-four time series equations were estimated, corresponding to the four aggregate crash categories and six highway categories. Each model was estimated based on the corresponding monthly crash counts prior to the speed limit change, and then used to predict expected post-change crash counts under the assumption that prior trends would continue without modification (i.e., that the speed limit change had no effect). Actual crash counts were then compared with the predicted counts, and a statistically significant difference between the two was taken as an indication that the speed limit change did in fact have an impact on safety. This time series analysis approach is known as Winter's additive method. Note that, in the application here, changes in VMT are not explicitly accounted for, although the effects of a steady traffic growth trend would be captured by the approach.

The analysis revealed that KABC crashes on rural interstates increased by a significant 16% in the 15 months following the speed limit change; changes in particular categories of crashes were not statistically significant, due in part to the smaller number of observations. On urban interstates, KA crashes increased by 75%, KAB crashes by 49% and KABC crashes by 28%; all these increases were statistically significant. On non-interstate rural multi-lane divided facilities, significant increases in all of the crash categories were observed following the speed limit change. Non-interstate urban multi-lane divided facilities gave mixed results by crash category. KAB and KABC crashes on non-interstate rural multi-lane undivided highways increased significantly, by 16% and 9% respectively, but no significant change was found in K or KA crashes. Finally, KA, KAB and KABC crashes on rural, two-lane US and State highways increased significantly following the speed limit change, but no significant change in fatal (K) crashes was detected.

Factors other than the speed limit increases were analyzed to determine if they might have contributed directly or indirectly to the observed changes in crash counts. These included the prevalence in reported crashes of DWI, truck involvement, speeding over the limit, driving at a speed unsafe for conditions, number of vehicles involved, darkness, wet road surface conditions, and snowy/icy road surface conditions. The involvement of these factors in injury crashes in comparable months in the periods before and after the speed limit change was examined.

Based on investigating police officer reports, there was no indication that crash-involved drivers were any more likely to be intoxicated after the speed limit increase than before. Similarly, there was no indication that trucks were more likely to be involved in crashes after than before. A smaller percentage of drivers were speeding over the limit following the change (as would be expected), but the number of drivers who were traveling at a speed unsafe for conditions was roughly the same before and after the change. Crashes involving multiple vehicles, during hours of darkness or on wet surfaces were all roughly comparable before and after the speed limit change. On the other hand, the prevalence of crashes in snowy/icy conditions increased following the change. It was not possible to determine the extent to which this increase resulted from unusually high exposure to snow and ice during the analysis period (and so would have happened independently of the speed limit change), and to what extent it resulted from the interactions between snowy/icy conditions and higher speed limits.

When the effect of snowy/icy conditions was accounted for in a re-analysis of the safety impacts, the formerly significant increase in KABC crashes on rural interstates and on rural multi-lane undivided highways became insignificant, and the estimated increases in other crash and highway categories, while remaining statistically significant, were reduced by zero to eight percentage points.

3.3 Survey of State Police Agencies

The project also conducted a limited a telephone-based survey of state police highway traffic law enforcement policies and decision processes, in order to determine how these may have changed following the NMSL repeal. The following sections describe the preparation and execution of the survey, and present the results that were obtained.

3.3.1 Survey Preparation and Execution

The telephone interviews were structured around a set of questions that were prepared to cover the topics of interest. However, the detailed conduct of the individual interviews was intentionally left flexible, in order to maximize the opportunities to elicit useful information and comments from the interviewees.

The initial contacts in this effort were with the police representatives identified by respondents in Section C of the survey of state DOTs. These individuals sometimes directed the survey personnel to someone else in the organization better able to answer the questions. It also turned out in a number of cases that the personnel recommended in the DOT surveys were no longer available. In these cases, project survey personnel attempted to identify and contact an alternative respondent in the state police agency, but this often proved to be a very inefficient and time-consuming process.

After a certain number of interviews had been conducted, the survey personnel found that each additional interview was simply repeating and confirming information that had been obtained in earlier ones. At that point, it was felt that the likelihood that an additional interview might produce new and useful information had become quite small. In view of the difficulty of identifying respondents in new agencies and of the project's resource constraints, it was decided to stop the survey.

3.3.2 Presentation of Survey Results

Surveys were successfully conducted with police officials in 18 states. The following table identifies the responding states and the main survey respondent in each.

Arkansas	Lt. Ray Coston
California	Mr. John Keller, California Highway Patrol
Florida	Major Ernesto Duarte
Georgia	Mr. Nigel Lange, Georgia State Patrol
Idaho	Glen Schwartz, Idaho State Police
Illinois	Sgt. Dianne Vanderkooy

Indiana	Major Thomas Melville
Iowa	Mr. Bob Thompson, Governor's Traffic Safety Bureau
Maryland	Sgt. Moore
Minnesota	Major Mike Asleson
Missouri	Captain Terry Moore
Nebraska	Major Anderson
New York	Major Jon Van Steenburg / Lt. Jon Tibbits
North Dakota	Major Mark Nelson
Oklahoma	Mr. Brandon Kopepasah, Dept. of Public Safety
Texas	Lt. Taylor and Major Gonzalez
Virginia	Mr. Cox, Virginia State Police
Washington State	Lt. Vasser

The discussions held with these respondents revealed a number of common features:

- The representatives interviewed stated that the primary goal of their agencies was the reduction of traffic fatalities and crashes. Speed limit enforcement decisions as well as allocations of patrols to other functions are made with this as the number one priority.
- Most respondents were not aware of any intentional change in their states' speed limit enforcement practices as a result of the NMSL repeal.
- Several respondents noted that the most significant change in enforcement practices after the repeal of the NMSL was a decrease in the speeding enforcement tolerance (i.e., drivers were formerly allowed to go some amount over the speed limit before getting a ticket, but this threshold was reduced as speed limits and driving speeds increased following the NMSL repeal).
- Where there were changes in enforcement patrol allocations after the repeal, these were generally the result of analysis of crash and fatality data, indicating the geographic areas or enforcement functions in which greater resources were needed.
- In many state agencies, the individuals who were involved in speed limit enforcement decision-making at the time of the NMSL repeal have retired or left the agency, and no institutional memory remains of the decision-making process that was followed at that time.

In addition to these common features, a number of individual responses provided interesting perspectives and insights.

California acknowledged that its speed limit enforcement decision-making was affected by the NMSL and its repeal. During the time that the NMSL was in effect, California had argued for less Federal control over speed limits. In addition to the philosophical point that setting speed limits is a state's right, California's argument was based on concerns about the NMSL impact on driver behavior (since most drivers were disobeying the speed limit, it decreased the overall respect for traffic laws), as well as about how it might distort police manpower allocation.

Specifically, California, like many other states, was concerned about Federal legislation authorizing sanctions (including reduced access to Federal construction funds) against states that inadequately enforced the NMSL. The threat of these sanctions could, for example, lead a governor to order the police to issue more speeding tickets in order to ensure that the state received its share of construction funds. After the NMSL repeal (including the relaxation of speed limits on rural interstates in 1987), there was no longer an incentive for an allocation of resources away from other types of traffic safety enforcement or other types of facilities.

It should also be recognized that enforcement policies and practices tend to change over time due to the natural development and improvement of decision-making methods, quite independently of the NMSL enactment or its repeal.

For example, Missouri noted that its speed limit enforcement decision-making process has changed since 1995, but not because of the NMSL repeal. Rather, this process has evolved to take advantage of the availability of better traffic safety statistics. Moreover, a Police Allocation Model developed at Northwestern University is now used to help in this process.

Similarly, in Washington State there was a change in enforcement-related decision-making in the late 1990s, but this change also does not appear to have been a direct result of the NMSL repeal. The new process in Washington makes systematic use of the traffic safety statistics maintained by the state DOT, together with time and activity reports completed by patrolling officers, to focus resources towards reducing crashes and fatalities caused by speed, DUI, seatbelt non-use and aggressive driving.

Interestingly, Minnesota has an anti-quota law that prevents law enforcement officials from giving police officers instructions on how many tickets to issue, and so limits the extent to which police officials at the state level can establish broad speed limit enforcement policies

The survey personnel also attempted to identify the extent to which political factors may influence speed limit enforcement allocations. In some states, this influence is quite open and transparent. For example, in Florida it was reported that police sometimes receive specific speed limit enforcement requests from local lawmakers. The police generally attempt to be responsive to such requests. However, if a major enforcement effort is not warranted, they tend to periodically revisit the locations in question, rather than mount a sustained enforcement program. In New York, the governor's Traffic Safety Committee can become involved in the process of determining speed limit enforcement allocations.

3.3.3 Conclusions from the Survey of State Police Agencies

More generally, to the extent that police agency budgets influence the feasibility of different enforcement efforts, and legislatures determine agency budgets, the agencies cannot be said to be totally isolated from political influences. Comments from Texas indicated this to be the case there. Washington State indicated that because the State Police Chief is appointed by the governor, and thus holds a somewhat political position, the decisions made in monthly executive staff meetings on enforcement might incorporate political input. Oklahoma indicated that some political influence results from the fact that the Legislature places a statewide cap on speed limits (of 75 mi/h), and then allows the municipalities or counties to set their individual speed limits. Overall, however, political influences on enforcement decisions seemed to be slight enough not to warrant significant comment by the representatives contacted for the survey.

3.4 Summary

This chapter has presented the design and results of surveys of State DOTs and State Police agencies conducted by the study. The survey of State DOTs also identified a number of documents that were prepared around the time of the NMSL repeal, to plan for and analyze the impacts of changed speed limits, and these reports were also reviewed in this chapter.

The results obtained and presented here are, for the most part, of a qualitative rather than quantitative nature. They do not contribute directly to the development of statistical models of the impacts of speed limits on speed choices, crash occurrence and/or crash severity. Nonetheless, the information gathered and insights gained from the surveys contributed to and guided the development of a number of the project's conclusions and recommendations.

4 Project Data Analyses

4.1 Overview of Analysis Approach and Model System

This chapter presents the statistical analyses of crash and crash-related data that were carried out during NCHRP project 17-23. This research represents the major portion of the project's efforts, and is a significant contribution to current scientific knowledge about motor vehicle crashes and factors that affect them.

As will be seen, analyses were carried out in a number of different research areas. In very general terms, the strategy for the overall research effort was based a high-level framework identifying the relationships between driver speed choice behavior, crash occurrence and or crash severity. These relationships are summarized in the following diagram:

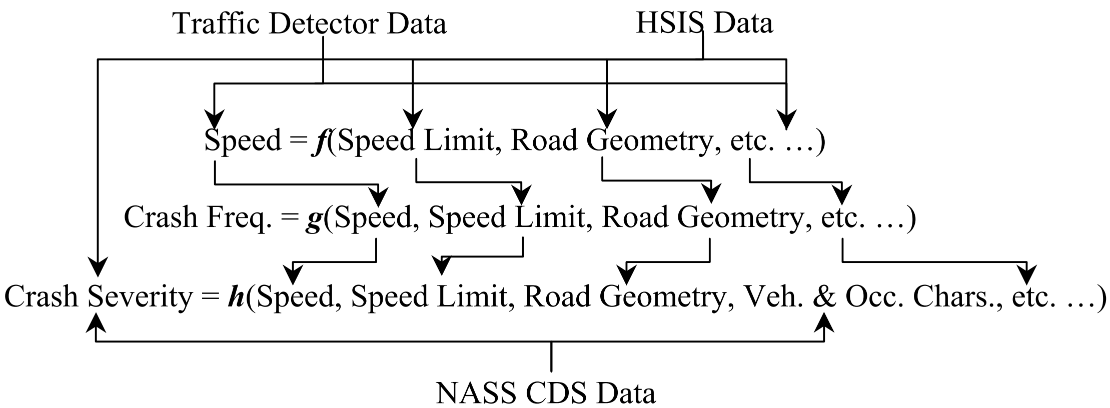

Figure 4-1 – A System of Sequential Regression Models

The ultimate goal of the project's research strategy was to clarify these various relationships and make them specific. The boxes in this diagram are intended to represent *generic* relationships between their inputs and outputs. Indeed, as will be seen below, during the course of the research a number of different specific models were developed and investigated for each of the boxes. Similarly, the inputs and outputs shown in the diagram should be understood as *generic* variable types; again, the different models developed during the project varied considerably in their specific inputs and outputs, with data availability frequently being the most significant constraint in determining which variables to include.

As can be seen from the diagram, the intent of the project was not to develop a single model that attempts to capture all the logical connections between crashes and their causes, but rather a system of inter-related models, each of which captures some part of the causal relations linking contributing factors and crash consequences. The inter-relationships between models mean that the outputs of one model in the system may be input to another model. For example, it is logical to think that the average speed and speed variability output by the speed choice model should be included among the inputs to the crash occurrence model; and that the average speed should be one of the inputs to the injury and crash severity model. Similarly, the crash occurrence model produces some measure of the incidence of crashes by type, and this should logically feed into the model that predicts a more detailed distribution of injury and crash severities.

With respect to the speed choice model, many of the factors that influence a roadway's traffic speed characteristics have been known for some time. The speed choice modeling work conducted in this project was designed to build on this prior understanding, but to place particular emphasis on the role of speed limits as they affect roadway speed characteristics. Moreover, the analysis work was planned to focus not only on average vehicle speeds, but also on vehicle speed variability, in order to be able to address the issues raised by the "variance kills" and similar hypotheses. Different models that were developed used different definitions of variability, depending on the nature of available measurements.

With respect to the crash occurrence model, one of the project's objectives was to investigate the influence of average speed and speed variability on the likelihood of crashes, either in total or distinguished by crash or injury severity. The hypothesis was that speed limits affect crash occurrence primarily through their effect on driver speed choices. The project was also interested in a variety of driver, roadway and environmental characteristics that may also affect crash likelihood.

The crash severity model differs from the crash occurrence model in that it predicts the distribution of crashes (or equivalently crash counts or rates) by crash or injury severity, given that a crash has already occurred. This model is not concerned with predicting the probability of crashes *per se*. Other factors that may influence the distribution of injury and crash severities are average speed (from the speed choice model), environmental characteristics, and vehicle characteristics, among others.

The process generally followed by the project was to identify, investigate and/or prepare datasets suitable for the estimation of the various model types; and then to specify, estimate and assess one or more models from each dataset.

It should be remembered that statistical relationship does not imply causality. Good model estimation results do not mean that the modeled phenomenon is *caused* by the "explanatory" variables, only that there is a statistical connection between them. Care must be taken to avoid drawing unwarranted conclusions about causality from modeling results. Terms such as "effect" or "impact" should be understood in the sense of association rather than causation.

As mentioned before, the availability of suitable data was the element that most determined the types of models that could be developed and the project's approach for developing them. Very specifically, the general lack of disaggregate speed data (i.e., speed measurements of individual vehicles, or of small groups of vehicles at very short time aggregations) for a wide variety of roadway segments over time (both before and after the speed limit changes) strongly influenced the nature of the speed choice models that were developed, and this in turn had repercussions on the development of the other models. In other cases, data were available to support the estimation of particular models, but the estimated models themselves were for various reasons judged to be unsatisfactory.

These data limitations, and the modeling problems that they created, ultimately constrained the extent to which the project could fill in and elaborate on the *complete framework* diagrammed above. It did not prove possible, using only the statistically valid models that resulted from the individual analyses, to construct a full model *system* incorporating all the hypothesized causal chains between speed limits and crash occurrence and severity. Nonetheless, as will be seen, the individual models that resulted from the development and assessment process, and the portions of the model system that they cover, do provide significant insights into the effects of speed limit changes, and into the factors that are associated with crash occurrence and severity. These insights, in turn, can be brought to bear on the central question of the project – the safety effects of speed limit changes on high-speed roads. This is done in Chapter 5.

The remainder of this chapter discusses in turn speed choice models (section 4.2), crash occurrence models (section 4.3), and crash and injury severity models (section 4.4). The chapter closes with a summary and discussion of the technical conclusions drawn from these analyses (section 4.5).

4.2 Speed Choice Models

The average speed chosen by drivers in a particular set of circumstances, and the variability of speed around this average, are key factors that influence crash probability and severity. Driver speed choice behavior is affected by posted speed limits, as well as by a wide variety of other factors related to the driver, the vehicle, the roadway and the roadway environment.

There are various types of data about driver speed choice behavior: the self-reported or observed behavior of individual drivers, results from theoretical models of speed choice behavior, and observations of the aggregate speed characteristics of a traffic stream. A number of different analyses of speed-related driver behavior were conducted, using most of these data types and applying a variety of analysis methods. These analyses included:

- An investigation of the determinants of highway driving speeds reported by respondents in the 2000 Motor Vehicle Occupant Safety Survey (section 4.2.1);
- A study of the average speed and speed variability on freeways in Orange County, California (section 4.2.2);
- An analysis of speed choices on highways in Austin, Texas (section 4.2.3);
- An ARIMA intervention analysis of the speed impacts of speed limit changes on highways in Washington State outside the northwest region (section 4.2.4); and
- Development of a theoretical model of rational speed choice, and numerical investigation of some of its properties (section 4.2.5).

Discussions of a number of other project speed choice analyses have been relegated to the appendices. These include analyses for which the limitations of the available data did not allow satisfactory conclusions to be drawn, and detailed technical descriptions of the methods used in some analysis components. Speed choice analysis material in the appendices includes:

- A description of the procedures used to estimate speed variables from Orange County traffic detector data (Appendix C);
- An analysis of speed choice in Washington State (Appendix D);
- An explanation of the methods applied to generate the synthetic datasets that were used to estimate the rational speed choice model (Appendix E).

4.2.1 Highway Driving Speeds Reported in the MVOSS

The 2000 Motor Vehicle Occupant Safety Survey (MVOSS) was conducted between November 2000 and January 2001, using random digit dialing and telephone interviews of persons age 16 or older residing in all 50 U.S. states and Washington D.C. (Boyle and Schulman 2001). The survey questions emphasized traffic safety issues, including crash exposure, travel choices (such as usual driving speed, driving frequency, seat belt use), and attitudes towards driving and current speed limits. Responses were obtained from 6,072 persons, and included basic demographic information about the respondent, as well as information about the type of vehicle that the respondent usually drove.

The project analyzed the 2000 MVOSS to obtain information about variables that may be important in influencing driver speed choice.

4.2.1.1 Data Preparation

After removing observations that lacked responses for key variables, the sample was reduced to complete records for 4,136 persons. Household income, which was categorized by value range in the original dataset, was converted into approximately continuous values using individual range mid-values.

Basic information about the data available from this survey is shown in Table 4-1.

Table 4-1 – Summary Statistics of 2000 MVOSS Data

Variables	Descriptions	Mean
Respondent Characteristics		
Age	Respondent age (years)	42.35
Income	Household income (in year 2000 US $)	54,851
Male	1 = male; 0 = female	0.5051
Hispanic	1 = Hispanic or Latino; 0 = otherwise	0.0897
Married	1 = married; 0 = otherwise: divorced, widowed, etc.	0.6368
College Educated	1 = possess a college education or higher; 0 = otherwise	0.6002
Employed	1 = employed or self-employed; 0 = otherwise	0.7123
Indicator for Central City	1 = living in a central city; 0 = otherwise	0.2671
Vehicle Characteristics		
Indicator for Passenger Car	1 = usually drive a passenger car	0.6057
Indicator for Van	1 = usually drive a van or minivan	0.0916
Indicator for Pickup	1 = usually drive a pickup truck	0.1655
Indicator for SUV	1 = usually drive an SUV	0.1142
Indicator for Heavy Truck	1 = usually drive a heavy truck	0.0138

Variables	Descriptions	Mean
Indicator for Other Vehicle	1 = usually drive other vehicles (i.e., not above vehicle types)	0.0039
Responses		
Driving Frequency	0 = drive a few days a month or a year (2.38%); 1 = drive a few days every week (9.37%); 2 = drive every day or almost every day (88.25%)	1.859
Seatbelt Frequency	0 = use seat belt rarely or never (1.80%); 1 = use seat belt some of the time (4.10%); 2 = use seat belt most of the time (9.52%); 3 = use seat belt all of the time (82.53%)	2.707
Seatbelt Law Support	0 = do not favor seat belt law at all (12.20%); 1 = favor seat belt law some (20.23%); 2 = favor seat belt law a lot (67.57%)	1.554
Speed Limit Support	0 = speed limits are too low (14.45%); 1 = speed limits are about right (77.37%); 2 = speed limits are too high (8.18%)	0.937
Opinion of Other Drivers	0 = other drivers are poor drivers (21.59%); 1 = other drivers are fair drivers (43.14%); 2 = other drivers are good drivers (30.09%); 3 = other drivers are excellent or very good drivers (5.19%)	1.189
Pressure to Exceed Speed Limit	0 = never feel pressure to exceed the speed limit (18.35%); 1 = rarely feel pressure to exceed the speed limit (30.32%); 2 = often feel pressure often to exceed the speed limit (34.91%); 3 = very often feel pressure to exceed the speed limit (16.41%)	1.506
Pass More	1 = I pass others more often than they pass me (31.98%)	0.3198
Pass Same	1 = I pass others as often as others pass me (2.66%)	0.0266
More Pass	1 = others pass me more often than I pass them (59.61%)	0.5961
Neither Pass	1 = neither (3.88%)	0.0388
Speed on Highway	Usual driving speed on highways (miles per hour)	64.48
Stopped by Police	1 = have been stopped by police in the last 12 months while driving	0.1893
Recent Traffic Ticket	1 = have received a ticket by police in the last 12 months while driving	0.1003
Drinking Days	Number of drinking days in the past 30 days	3.6649
Number of Drinks	Average # drinks per drinking day	1.609
Drinking and Driving Days	Number of drinking-and-driving days in the past 30 days	0.5091
Injured in Crash	1 = have been injured in a crash (as a driver, occupant or non-occupant)	0.2953
Injured as Driver	1 = have been injured as a driver at some point in the past	0.2542
Number of Injury Events	Number of times having been injured in a crash (as a driver, occupant or non-occupant)	0.4444

It can be seen that several of the MVOSS variables involve responses to questions about personal preferences (e.g., support for seat belt laws) and sensitive behaviors (e.g., number of drinking days per month and speed choice). For a variety of reasons, the responses given to such questions may not accurately reflect the respondent's actual opinion or behavior. (Corbett [2001] and Bradburn and Sudman [1979] discuss these issues and their treatment in survey design.) Such effects can bias the reported survey results (e.g., biasing downward the estimates of drinking and driving, and upward the estimated level of support for speed laws[14]) and affect conclusions drawn from analyses of the data. The possibility of such biases must be kept in mind when using this data source.

4.2.1.2 Model Estimation and Analysis

Table 4-2 presents estimation results for an ordinary linear regression model of the reported usual highway driving speeds as a function of some of the explanatory variables available in the MVOSS dataset. The table presents an initial model that includes all the variables considered, as well as a final model that incorporates only those variables for which the coefficient estimates were found to be statistically significant at the p=0.10 level.

As can be seen, individuals' the usual highway driving speeds that individual report are predicted to increase with household income, drinking amount and frequency, recent traffic violations and recent experiences with roadway police. Male drivers, drivers with a college education, frequent drivers and drivers in central cities also tend to drive at higher speeds. Age and employment status are estimated to reduce chosen driving speeds.

Note that the MVOSS asks respondents about the total income of their household rather than their individual income or wage. Interestingly, the model's linear plus quadratic household income terms show that the influence of household income on speed choice reaches a maximum at around $130,000 per year (in year 2000 dollars). One may hypothesize that higher values of travel time, due to higher wages and income, result in higher speed choices. Of course, such travel time values may also result in higher values of life, thus offsetting value of time effects to some extent.

Figure 4-2 illustrates relationships between driver characteristics (including gender, household income and residence location) and the predicted usual highway driving speed.

Table 4-2 – Linear Regression Model of Usual Driving Speed

Variables	Initial Model			Final Model		
	Coeff.	Std.Err.	P-value	Coeff.	Std.Err.	P-value
Constant	64.0581	1.0677	0.0000	63.3613	0.7546	0.0000
Male	0.8307	0.2361	0.0004	0.8541	0.2198	0.0001
Age	-0.0846	0.0402	0.0355	-0.0419	7.839E-03	0.0000
Age Squared	0.0004	4.241E-04	0.3051			
Hispanic	-0.7401	0.3778	0.0501	-0.7340	0.3752	0.0504
Married	0.3063	0.2501	0.2206			
College Educated	1.1610	0.2324	0.0000	1.1627	0.2288	0.0000
Employed	-0.6430	0.2769	0.0202	-0.7075	0.2589	0.0063
Income	5.076E-05	1.269E-05	0.0001	5.203E-05	1.233E-05	0.0000
Income Squared	-2.020E-10	8.358E-11	0.0156	-2.090E-10	8.210E-11	0.0109
Indicator for Central City	1.3391	0.2430	0.0000	1.3134	0.2405	0.0000

[14] For example, 82.5% of MVOSS respondents reported that they used their vehicle shoulder belt all of the time, and 9.5% reported that they used the belt most of the time. In contrast, NHTSA's (2001) National Occupant Protection Use Survey staff found that only 69% to 76% of adults (across several age categories) were wearing shoulder belts at 12,000 intersections during daylight hours in the year 2000.

Indicator for Van	-0.2913	0.3771	0.4399			
Indicator for Pickup	-0.3052	0.3138	0.3307			
Indicator for SUV	-0.0861	0.3485	0.8048			
Indicator for Heavy Truck	-0.4012	0.9354	0.6680			
Indicator for Other Vehicle	-1.8403	1.7131	0.2827			
Driving Frequency	1.5182	0.2791	0.0000	1.4622	0.2775	0.0000
Seatbelt Frequency	0.1495	0.1584	0.3451			
Seatbelt Law Support	-0.3040	0.1653	0.0660			
Speed Limit Support	-1.3052	0.2392	0.0000	-1.3743	0.2369	0.0000
Opinion of Other Drivers	-0.0023	0.1304	0.9859			
Pressure to Exceed Speed Limit	0.3690	0.1134	0.0011	0.3594	0.1123	0.0014
More Passed	-4.5112	0.2541	0.0000	-4.5226	0.2515	0.0000
Neither Pass	-2.4872	0.5673	0.0000	-2.5151	0.5635	0.0000
Pass Same	-1.9408	0.6644	0.0035	-1.8567	0.6620	0.0050
Stopped by Police	0.9788	0.3818	0.0104	0.9598	0.3773	0.0110
Recent Traffic Ticket	0.8391	0.4901	0.0869	0.8827	0.4855	0.0690
Drinking Days	0.0285	0.0188	0.1304	0.0328	0.0175	0.0604
Number of Drinks	0.2796	0.0656	0.0000	0.2881	0.0648	0.0000
Drinking and Driving Days	0.0375	0.0528	0.4776			
Injured in Crash	0.8872	0.5734	0.1218			
Injured as a Driver	-0.7707	0.5630	0.1710			
Number of Injury Events	-0.0924	0.1511	0.5409			
Nobs.	4136			4136		
R-sqrd.	0.2278			0.2258		
Adj. R-sqrd.	0.2218			0.2224		

Note: Some coefficient estimates were omitted to simplify the presentation here. See Kweon and Kockelman (2003a) for further details.

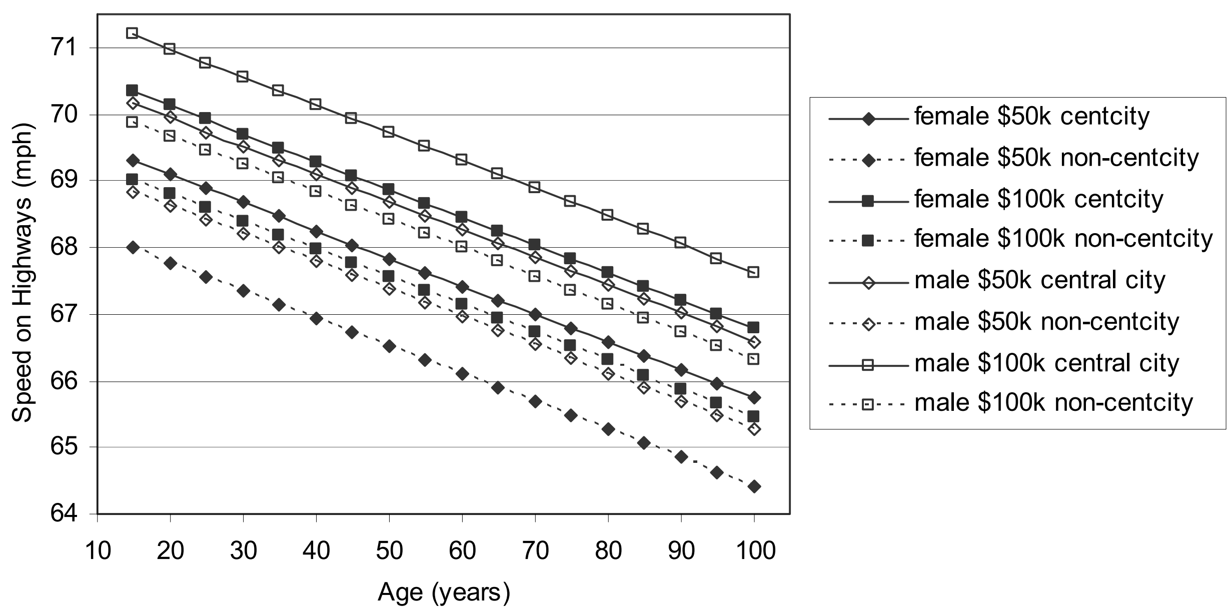

Figure 4-2 – Usual Driving Speed *vs.* Driver Characteristics
Note: The reference individual is non-Hispanic, married, college-educated, and employed, and exhibits average values of all other explanatory variables included in the final model of Table 4-2.

The MVOSS also included questions regarding respondents' attitudes about the appropriateness of the current level of speed limits (i.e. whether they were too low, too high or about right). It was found that 76.6% of the respondents were satisfied with current speed limits, 16.2 % felt they were too low, and 7.2% thought they were too high. The project analyzed the responses to these questions as well, and developed an ordered probit model of opinion regarding higher speed limits as a function of respondent characteristics. This analysis is presented in Appendix B. Other results and conclusions derived from the MVOSS dataset can be found in Kweon and Kockelman (2003a).

4.2.2 Speed Choice on Orange County Freeways

Using the Traffic Accident Surveillance and Analysis System (TASAS) database maintained by the California Department of Transportation, Golob and Recker (2002) acquired crash data for 9,341 crashes (around 78% of the total) on six freeways (I-5, SR-22, SR-55, SR-57, SR-91 and I-405) in Orange County in 1998. Golob and Recker then merged the data on each crash with traffic data from the nearest two upstream and two downstream single-loop traffic detector stations during a period from 30 minutes before to 15 minutes after the reported crash time. Each detector station produced measurements of count and occupancy data by direction and lane, accumulated and output at 30-second intervals.

Golob and colleagues have used essentially this dataset to create a typology of traffic crashes related to traffic flows and detector occupancies, weather and lighting conditions (Golob and Recker 2002; Golob and Recker 2003; Golob, Recker, and Alvarez 2003a; and Golob, Recker, and Alvarez 2003b). Their work relies on cluster analysis, and speeds play only a minor role.

These researchers kindly granted the project access to the dataset that they compiled. The dataset was particularly interesting for the purposes of this project because of its inclusion of relatively detailed traffic data near the location of and around the time of reported crashes.

4.2.2.1 Data Preparation

The project focused on injury and fatal crashes in January 1998. From the database for these crashes, traffic data from detector stations within 2,000 feet (almost one-half mile) upstream of each crash site[15] was extracted. Traffic data for the 30 minutes prior to the reported crash time was considered. However, since the actual time of a crash is usually not precisely known, traffic data recorded in the 2.5 minutes prior to reported crash times was discarded, consistent with Golob and Recker (2002), who did so as well. In this way, data on 55 crashes were obtained.

Although the dataset did not include vehicle speeds, these can be estimated from the outputs of a single-loop detector through a calculation that involves a parameter known as the *g-factor*, which is the inverse of the mean effective length of vehicles activating the detector. A vehicle's effective length accounts for its true vehicle length plus an additional length due to the fact that a loop's detection zone extends beyond its actual physical extent. G-factors can be empirically

[15] A distance of 2,000 feet was chosen since, at speeds of 60 mi/h, vehicles could reach the crash site within 30 seconds. It is expected that traffic conditions so close to the crash sites will be a reasonable reflection of traffic conditions at the crash site itself.

determined for a given loop detector and traffic mix, but this level of information was not available to us. A reasonable value for the mean effective vehicle length was assumed based on g-factor values reported in Jia *et al*. (2001), and the average speed of vehicles using each lane in each 30-second interval was thereby estimated.

Speed standard deviations were estimated by assuming that speed distributions are stationary across each set of five successive 30-sec intervals and assessing the variation in these 30-sec samples. In reality, speed profiles change over time, and so these assumptions lead to standard deviation estimates that are biased upwards. However, there is no other way to uncover speed variation information for individual vehicles when the individual vehicle data are lost during the 30-sec data accumulation by the detector algorithms. This is the best that the project feels can be done with such data.[16] A detailed description of the project's methods for computing average speed and speed standard deviation is provided in Appendix C. Using short-duration measurements from radar guns, the project also obtained and analyzed individual vehicle speed data for several highways in Austin, Texas, as described in Section 4.2.3.

The computation of speed standard deviation results in the loss of the first two observations for each lane at each station. As a result, the data for the models of speed and speed variation consisted of 53 sequential 30-second observations from loop detector stations within 2000 feet upstream of the 55 crash sites. After removing approximately 2% of observations affected by incomplete traffic recordings, 2,858 30-second observations from loop detector stations were left. Each such observation was assumed to apply over the road segment on which the station was located.

Since the project was interested in within-lane as well as segment-specific speed information, two sets of data were compiled: one that was segment specific and reflected conditions across all lanes at a detector station, and the other that was lane-specific. The latter contained over 12,000 observations, and included each station's detector outputs for each of three or more lanes per direction. To identify lane-specific data, variables indicating the number of lanes and the lane position (e.g., inside, next to inside, middle lane) were appended. The crash dataset provided information on lighting and other environmental conditions. While the speed limits of all the segments were 65 mi/h, there was some variation in their design speeds, as provided in the California HSIS dataset. Table 4-3 presents summary statistics for the segment-specific variables that were used in the analyses, while Table 4-4 presents these statistics for the lane-specific variables.

Table 4-3 – Summary Statistics of Segment-Level Variables in the Orange County Dataset

Variables	Description	Min.	Max.	Mean	Std. Dev.
SDSXNSPD	Std. deviation of speed across & within lanes (30-sec)	0	123.28	10.83	10.02
SDLNS	Std deviation of speed across lanes (30-sec)	0	107	7.88	9.88
VBARSXN	Average vehicle speeds across lanes (30-sec)	0	123.06	42.89	22.05
TMTLCRSH	The time of crash minus the time of the observation (sec)	120	1680	900.08	458.94
FOURLN	1 if the roadway has 4 lanes per direction, 0 otherwise	0	1	0.44	0.50

[16] The project reviewed much literature on the aggregation of traffic data (e.g., Pushkar et al. 1994, Wang and Nihan 2000, Coifman et al. 2001, Coifman 2001, and Hellinga 2002). No better solution was found than the one that the project developed.

ABVFOUR	1 if the roadway has more than 5 lanes per direction, 0 otherwise	0	1	0.39	0.49
DUSKDAWN	1 if crash occurred during dusk or dawn, 0 otherwise	0	1	0.02	0.14
DARKSTRL	1 if crash occurred at night with street light, 0 otherwise	0	1	0.19	0.39
DARKNOSL	1 if crash occurred at night without street light, 0 otherwise	0	1	0.30	0.46
WET	1 if crash occurred when the roadway was wet, 0 otherwise	0	1	0.35	0.48
OBSTRUCT	1 if crash occurred when there was an obstruction on the roadway, 0 otherwise	0	1	0.02	0.14
CONSTRUC	1 if crash occurred in construction zone, 0 otherwise	0	1	0.13	0.34
CRTIME3	if TMTLCRSH <= 3 min then TMTLCRSH else 0 (min)	0	180	8.50	35.18
CRTIME5	if TMTLCRSH <= 5 min then TMTLCRSH else 0 (min)	0	300	27.77	74.43
CRTIME10	if TMTLCRSH <= 10 min then TMTLCRSH else 0 (min)	0	600	115.31	187.41
DSGN_SPD	Design speed (mi/h)	60	70	69.82	1.35
VOLUME	Sum of traffic counts across lanes (30-sec)	0	83	32.18	19.94
DENSITY	#vehicles per lane per mile	.00	144.47	23.88	21.58
VC_RATIO	The ratio of traffic volume to the segment capacity	.00	1.25	.47	.30
Nobs. = 2,858					

Table 4-4 – Summary Statistics of Lane-Level Variables in the Orange County Dataset

Variables	Description	Min.	Max.	Mean	Std. Dev.
SDLNSPD	Std. deviation of speed within one lane (30-sec)	0	87.78	6.60	6.99
VBAR	Average vehicle speeds (30-sec)	0	305.05	42.72	28.71
VC_RATIO	The ratio of traffic volume of a lane to the its capacity	0	1.25	0.46	0.29
VOL	Traffic count for all lanes in 30-sec period	0	30	7.68	6.02
OCC	Occupancy in a 30-second period	0	1	0.20	0.29
TMTLCRSH	The time of crash minus the time of the observation (sec)	120	1680	899.34	458.89
RGHTSIDE	1 if the lane is the far right side lane, 0 otherwise	0	1	0.23	0.42
NXT2RGSD	1 if the lane is the next-to-right-side lane, 0 otherwise	0	1	0.23	0.42
MIDDLELN	1 if the lane is the middle lane, 0 otherwise	0	1	0.13	0.34
NXT2INSD	1 if the lane is the next-to-inside lane, 0 otherwise	0	1	0.24	0.43
INSIDELN	1 if the lane is the inside lane, 0 otherwise	0	1	0.24	0.43
FOURLN	1 if the roadway has 4 lanes per direction, 0 otherwise	0	1	0.41	0.49
ABVFOUR	1 if the roadway has more than 5 lanes per direction, 0 otherwise	0	1	0.47	0.50
DUSKDAWN	1 if crash occurred during dusk or dawn period, 0 otherwise	0	1	0.02	0.13
DARKSTRL	1 if crash occurred at night with street light, 0 otherwise	0	1	0.19	0.39
DARKNOSL	1 if crash occurred at night without street light, 0 otherwise	0	1	0.32	0.47
WET	1 if crash occurred when roadway was wet, 0 otherwise	0	1	0.37	0.48
OBSTRUCT	1 if crash occurred when there was roadway obstruction, 0 otherwise	0	1	0.01	0.11
CONSTRUC	1 if crash occurred in construction zone, 0 otherwise	0	1	0.14	0.34
CRTIME3	if TMTLCRSH <= 3 min then TMTLCRSH else 0 (min)	0	180	8.50	35.17
CRTIME5	If TMTLCRSH <= 5 min then TMTLCRSH else 0 (min)	0	300	27.71	74.34
CRTIME10	if TMTLCRSH <= 10 min then TMTLCRSH else 0 (min)	0	600	115.73	187.69
DSGN_SPD	Design speed (mi/h)	60	70	69.83	1.30
DENSITY	#vehicles per lane per mile	0	237.42	22.87	26.99
Nobs. = 12,243					

4.2.2.2 Model Estimation and Analysis

Using the Orange County data described above, ordinary and weighted least squares regression analyses of average speed and speed variation on the subject freeways were conducted.

The tables showing regression results (Tables 4-5 through 4-8) contain both initial model and final model results. Initial models included all explanatory variables of any interest; final models retained only those variables remaining statistically significant at the p=0.10 level. Elasticity estimates are also shown for final results.[17]

These analyses indicate that higher speeds correspond to higher speed variability (as measured by the estimates of speed standard deviation, both within and across lanes), even after controlling for a host of factors; these relationships are apparent from the coefficients of VBAR in Table 4-5 and Table 4-7. Working with these 30-second observations, vehicle speeds or speed variation were not found to increase near the time of crash. However, much can happen in 30 seconds: a crash due to speed variation may require just two extreme vehicle speeds, the data for which can be obscured by the tens of vehicles that cross a set of lane detectors in a 30-sec interval.

Table 4-5 – Linear Regression Model of Speed Variation Within Lanes

Variables	Initial Model				Final Model				
	Coef.	S.e	Std. Coef.	P-value	Coef.	S.e.	Std. Coef.	P-value	Elasticity
CONSTANT	-8.151	2.950		.006	-8.369	2.944		.004	
FOURLN	.873	.180	.086	.000	1.050	.117	.103	.000	0.0277
ABVFOUR	-.250	.195	-.024	.199					
DUSKDAWN	-1.771	.342	-.053	.000	-1.751	.342	-.053	.000	-0.2563
DARKSTRL	3.059	.157	.202	.000	3.063	.157	.202	.000	0.2803
DARKNOSL	.456	.121	.040	.000	.446	.120	.039	.000	0.0249
WET	1.014	.121	.093	.000	.990	.120	.091	.000	0.0399
OBSTRUCT	5.738	.478	.120	.000	5.856	.469	.123	.000	0.8642
CONSTRUC	1.257	.184	.074	.000	1.212	.180	.072	.000	0.1337
VBAR	0.0550	.004	.213	.000	0.0.46	.004	.212	.000	0.3537
RGHTSIDE	1.446	.216	.118	.000	1.593	.182	.130	.000	0.1299
NXT2RGSD	1.066	.169	.092	.000	1.167	.149	.100	.000	0.0951
MIDDLELN	1.001	.171	.071	.000	1.080	.160	.077	.000	0.1214
NXT2INSD	-.617	.171	-.053	.000	-.504	.147	-.043	.001	-0.0403
INSIDELN	-.587	.211	-.050	.005	-.441	.177	-.037	.013	-0.0351
DSGN_SPD	.139	.042	.032	.001	.139	.042	.032	.001	1.4707
CRTIME3	4.196E-04	.002	.003	.783					
CRTIME5	-4.823E-04	.001	-.007	.508					
CRTIME10	3.674E-04	.000	.014	.161					
DENSITY	9.462E-03	.003	.046	.003	9.551E-03	.003	.047	.003	0.0331
R-sqrd.				.119					.118
Adj. R-sqrd.				.117					.117
Nobs.				12,243					12,243
Dependent Variable: SDLNSPD Weighted Least Squares Regression - Weighted by VOL									

[17] An elasticity expresses the percentage change in a dependent variable resulting from a 1% change in an associated explanatory variable.

Interestingly, the DSGN_SPD variable consistently has the strongest association with all response variables studied: all elasticities were estimated to be above 1.0 even after controlling for average observed speeds in the speed variance models. Design speed is a proxy for sight distance, degree of horizontal curvature, and other design attributes on segments where design governs the safe driving speed. Design speed may also be a proxy for an upper bound on speed limits. Although speed limit data were not available in this dataset, it is reasonable to conjecture that all segments had similar posted limits since they were located on similar high-type facilities.

Results in Table 4-6 suggest that higher speeds tend to occur on four-lane and five-lane (one-way) freeways more than on three-lane freeways. This is consistent with *Highway Capacity Manual* (TRB 2000) formulae, which indicate that free-flow speeds (FFS) rise with the number of lanes (up to a total of 5 lanes in one direction). In the Orange County model results, vehicles travel an average of 2.2 mi/h faster on four-lane compared to three-lane freeways, and vehicles on five-lane freeways travel an average 3.8 mi/h faster than those on three-lane freeways. (The corresponding estimates for basic freeway segments in HCM Chapter 23 are 1.5 and 3.0 mi/h.)

While higher speeds correspond to greater speed variation, and more lanes correspond to higher speeds, the largest standard deviation in speeds is estimated to occur on four-lane sections, as implied by the coefficients on the indicator variables FOURLN and ABVFOUR in Table 4-5.

It can also be seen from Table 4-5 that the highest standard deviations tend to occur in the far right-side (RGHTSIDE) lane. This makes sense, given the speed changes that many vehicles must make in right-side auxiliary lanes (particularly if on- and off-ramps are of the parallel rather than tapered type); moreover, many special, slow vehicles (such as overloaded trucks and vehicles pulling trailers) choose the far-right lane. As shown in Table 4-6, the lowest speeds tend to occur in the next-to-right-side (NXT2RGSD) lane. This may be because those lanes host a great many weaving maneuvers between on and off ramps, particularly if they lie alongside an auxiliary lane joining such facilities.

As one might expect, the inside lanes have the highest average speeds (Table 4-6). The inside lane is chosen for overtaking/passing other vehicles and may be a special (e.g. HOV) lane. In addition, speeds are lowest at night on freeways where lighting is not provided; as expected, they are highest during the daytime (Table 4-6).

These regression results also suggest that higher traffic density corresponds to lower average speeds (Table 4-6) and to lower overall speed standard deviations (Table 4-7), but also to higher speed standard deviations within each lane (Table 4-5). The higher within-lane speed variation result may be due to drivers having less opportunity to change lanes when traffic densities are high, while the opposite result for across-lane speed variability may result from congested conditions that create an overall stability in speeds across lanes. This result may suggest more within-lane crashes when densities are high (due to higher speed variations within lanes). Higher densities mean tighter gaps for lane changes, suggesting a potential for more crashes across lanes as well, even though speeds are relatively similar across lanes.

Table 4-6 – Linear Regression Model of Average Speed Within Lanes

Variables	Initial Model				Final Model				
	Coef.	S.e.	Std. Coef.	P-value	Coef.	S.e.	Std. Coef.	P-value	Elasticity
CONSTANT	30.021	7.446		.000	29.790	7.437		.000	
FOURLN	2.126	.455	.054	.000	2.156	.452	.055	.000	0.0088
ABVFOUR	3.837	.491	.097	.000	3.811	.481	.096	.000	0.0054
DUSKDAWN	.566	.864	.004	.512					
DARKSTRL	-3.477	.396	-.059	.000	-3.516	.390	-.060	.000	-0.0497
DARKNOSL	-4.730	.301	-.107	.000	-4.748	.294	-.108	.000	-0.0409
WET	-4.781	.302	-.113	.000	-4.723	.288	-.112	.000	-0.0294
OBSTRUCT	-9.096	1.203	-.049	.000	-9.094	1.203	-.049	.000	-0.2073
CONSTRUC	-0.0514	.464	-.001	.912					
RGHTSIDE	-1.093	.544	-.023	.045	-1.098	.544	-.023	.043	-0.0138
NXT2RGSD	-2.162	.426	-.048	.000	-2.164	.426	-.048	.000	-0.0273
MIDDLELN	1.689	.432	.031	.000	1.686	.432	.031	.000	0.0293
NXT2INSD	3.551	.431	.078	.000	3.541	.431	.078	.000	0.0438
INSIDELN	5.254	.530	.115	.000	5.247	.529	.115	.000	0.0646
DSGN_SPD	.623	.106	.037	.000	.626	.106	.037	.000	1.0233
CRTIME3	-2.257E-03	.004	-.004	.557					
CRTIME5	-2.777E-04	.002	-.001	.880					
CRTIME10	1.687E-04	.001	.002	.799					
DENSITY	-.617	.005	-.780	.000	-.617	.005	-.781	.000	-0.3303
R-sqrd.				.626					.626
Adj. R-sqrd.				.625					.625
Nobs.				12,243					12,243
Dependent Variable: VBAR Weighted Least Squares Regression - Weighted by VOL									

Table 4-7 – Linear Regression Model of Variation in Average Within-Lane Speed Across All Lanes

Variables	Initial Model				Final Model				
	Coef.	S.e.	Std. Coef.	P-value	Coef.	S.e.	Std. Coef.	P-value	Elasticity
CONSTANT	42.769	6.640		.000	42.086	6.561		.000	
FOURLN	-.228	.331	-.016	.492					
ABVFOUR	-8.178	.358	-.574	.000	-7.931	.256	-.557	.000	-0.2233
DUSKDAWN	-4.047	.772	-.089	.000	-3.902	.730	-.086	.000	-0.4783
DARKSTRL	.604	.355	.029	.089	.691	.342	.033	.044	0.0552
DARKNOSL	1.314	.286	.082	.000	1.315	.284	.082	.000	0.0681
WET	.216	.276	.014	.433					
OBSTRUCT	-.889	1.075	-.014	.408					
CONSTRUC	-1.466	.418	-.063	.000	-1.492	.416	-.064	.000	-0.1401
VBARSXN	-.135	.010	-.347	.000	-.136	.009	-.351	.000	-0.7403
DSGN_SPD	-.305	.097	-.052	.002	-.296	.096	-.050	.002	-2.6231
CRTIME3	3.158E-03	.003	.016	.360					
CRTIME5	-4.306E-04	.002	-.005	.794					
CRTIME10	2.310E-04	.001	.006	.698					
DENSITY	-.169	.009	-.479	.000	-.170	.009	-.481	.000	-0.4934
R-sqrd.				.368					.368
Adj. R-sqrd.				.365					.366
Nobs.				2,858					2,858
Dependent Variable: SDLNS Weighted Least Squares Regression - Weighted by VOLUME									

While design speeds do not vary much across the set of sites (almost all[18] are 70 mi/h), higher design speeds are associated as expected with higher average speeds (Table 4-9), but also with higher speed standard deviations (Table 4-5). This is an interesting result: while the data are 30 sec aggregations of individual vehicle data, and the calculations applied to estimate speed variations involve some heroic assumptions, higher design speeds may be associated with more and more severe crashes through greater variation in speed choices and higher speeds.

The results of Table 4-8 suggest that traffic on five-lane freeways experiences higher overall (across- plus within-lane) speed variation than traffic on three- and four-lane freeways. This may be because drivers have more freedom to choose their preferred speeds on freeways with more lanes.

Road conditions and environmental variables were also found to be statistically significant explanatory variables in these models. The coefficients associated with the variable WET in Table 4-5 and Table 4-6 suggest that people drive more slowly on wet roads and with higher variations in speeds. However, the variable WET was estimated to reduce total standard deviation in speeds. The presence of obstructions tends to reduce speeds substantially but to increase speed variation. These results seem very reasonable.

Table 4-8 – Linear Regression Model of Total Speed Variation Across and Within Lanes

Variables	Initial Model				Final Model				
	Coef.	S.e.	Std. Coef.	P-value	Coef.	S.e.	Std. Coef.	P-value	Elasticity
CONSTANT	-7.878	7.439		.290	-7.692	7.342		.295	
FOURLN	.213	.371	.013	.566					
ABVFOUR	9.724	.401	.587	.000	9.610	.294	.580	.000	0.1970
DUSKDAWN	-.405	.865	-.008	.639					
DARKSTRL	2.500	.398	.104	.000	2.474	.383	.103	.000	0.1439
DARKNOSL	.204	.320	.011	.524					
WET	-1.938	.309	-.111	.000	-1.999	.294	-.115	.000	-0.0546
OBSTRUCT	2.752	1.204	.036	.022	2.545	1.166	.033	.029	0.2261
CONSTRUC	-3.065	.468	-.114	.000	-2.999	.454	-.111	.000	-0.2049
VBARSXN	7.995E-02	.011	.177	.000	0.0779	.010	.172	.000	0.3085
DSGN_SPD	.178	.108	.026	.101	.179	.107	.026	.094	1.1542
CRTIME3	1.606E-03	.004	.007	.678					
CRTIME5	2.963E-04	.002	.003	.873					
CRTIME10	-5.369E-04	.001	-.012	.421					
DENSITY	-5.754E-02	.010	-.140	.000	-0.059	.010	-.144	.000	-0.1246
R-sqrd.	.414				.413				
Adj. R-sqrd.	.411				.411				
Nobs.	2,858				2,858				
Dependent Variable: SDSXNSPD Weighted Least Squares Regression - Weighted by VOLUME									

[18] Rather remarkably, there were no 65 or 75 mi/h design speed sections in this dataset.

Table 4-9 – Linear Regression Model of Average Speed Across All Lanes

Variables	Initial Model				Final Model				
	Coef.	S.e.	Std. Coef.	P-value	Coef.	S.e.	Std. Coef.	P-value	Elasticity
CONSTANT	-70.530	13.668		.000	-71.188	13.649		.000	
FOURLN	1.928	.684	.053	.005	1.719	.482	.048	.000	0.0045
ABVFOUR	.204	.741	.006	.783					
DUSKDAWN	1.938	1.596	.017	.225					
DARKSTRL	-4.522	.729	-.085	.000	-4.750	.717	-.089	.000	-0.0698
DARKNOSL	-8.464	.567	-.205	.000	-8.254	.544	-.200	.000	-0.0785
WET	-4.980	.562	-.129	.000	-4.811	.529	-.125	.000	-0.0332
OBSTRUCT	-8.353	2.217	-.050	.000	-8.708	2.161	-.052	.000	-0.1953
CONSTRUC	1.401	.864	.023	.105					
DSGN_SPD	2.081	.196	.137	.000	2.096	.196	.138	.000	3.4125
CRTIME3	-5.525E-03	.007	-.011	.438					
CRTIME5	-3.259E-03	.003	-.013	.340					
CRTIME10	6.444E-04	.001	.007	.601					
DENSITY	-.705	.012	-.776	.000	-.709	.012	-.781	.000	-0.3781
R-sqrd.				.591					.590
Adj. R-sqrd.				.589					.589
Nobs.				2,858					2,858
Dependent Variable: VBARSXN Weighted Least Squares Regression - Weighted by VOLUME									

Binomial models (coding as 1 a crash occurrence within some short time period) were also estimated to investigate the likelihood of crash occurrence as a function of the variables available in the Orange County dataset. However, crash occurrence could not be statistically related to any of the available variables. This may have been because the data aggregation obscured individual speed choices, and because the actual crash times may have differed by several minutes or more from those recorded by police officers. Thus, the time-till-crash variables (for 3, 5 and 10 minutes preceding the reported crash times) were not nearly as helpful as had originally been expected, in any of the models.

4.2.3 Speed Choice in Austin, Texas

To complement the models of speed choice and speed variation that appear elsewhere in this section, a limited set of individual vehicle speed observations were collected using a radar gun on a variety of high-speed highways in Austin, Texas. As in Section 4.2.2, weighted least squares (WLS) models were developed to assess the effects of flow, number of lanes, and other variables on average speed and speed standard error.[19] However, the measures of average speed and speed standard error were based here on individual vehicle measurements by the radar device, rather than on time aggregations of 30-second loop detector data. This was, in fact, the only dataset containing individual vehicle measurements that was available to the project.

[19] Standard error is an estimate of the true standard deviation, involving division of observed squared deviations from the mean by *n*-1, where *n* is the number of speeds observed in the observation interval.

4.2.3.1 Data Preparation

The data used for this analysis were collected from 16 high-speed roadway sites around the greater Austin region. Care was taken to make observations at a diverse set of sites, varying in their speed limit, number of lanes, freeway versus non-freeway status, and urban versus rural character. The observers noted as many vehicle speeds as would register on their radar gun over roughly 120 time intervals[20] at each site, resulting in 1,766 observations. The interval lengths varied from 5 to 20 seconds, depending on the traffic flow at the site. Vehicle counts in each interval were totaled, and equivalent flow rate values (in units of vehicles per hour per lane) were generated.

Table 4-10 provides summary statistics for the dataset of speed observations and site characteristics. It is evident that the dataset contains a good mix of explanatory variables. However, one major limitation is that the data come from a cross-section of roadways for which the speed limits did not change during the time of observation. It is not known with certainty whether, in a static situation such as this, a speed limit's effect will be similar to its effect in a more dynamic situation where speed limits may vary over time.

4.2.3.2 Model Estimation and Analysis

Weighted least squares (WLS) regression models were chosen for both the average speed and speed standard error models. The number of records read from the radar gun was used as the observation weight, because the variation in average speed should theoretically vary inversely with count, and the variation in the speed standard error should vary approximately inversely with the count.

While this first relationship is well known (i.e. Var(mean(X)) = Var(X)/n), the variation in standard error calculations is less well known. This relationship can be seen as follows:

Given that $s = \hat{\sigma} = \sqrt{\dfrac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$ and assuming that the x values (speeds in this context) are normally distributed, it is well known that $\dfrac{(n-1)s^2}{\sigma^2} \sim \chi^2_{n-1}$ where the subscript *n-1* denotes the number of degrees of freedom of this chi-squared distribution. Then

$$V(s) = E(s^2) - E\left(s\right)^2 = \sigma^2 - E\left(\sqrt{\frac{\sigma^2 \cdot \chi^2_{n-1}}{n-1}}\right)^2 = \sigma^2 - \frac{\sigma^2}{n-1}E\left(\sqrt{\chi^2_{n-1}}\right)^2$$

The square root of a chi-squared distribution with n degrees of freedom is a chi distribution with the same degrees of freedom, denoted here as χ_n (Weisstein 2005).

[20] For sites 14 through 16, fewer time intervals were observed.

It is also known that $E\left(\chi_n\right)=\dfrac{\sqrt{2}\Gamma\left(\frac{1}{2}(n+1)\right)}{\Gamma\left(\frac{1}{2}n\right)}$

where *Γ(·)* denotes the gamma function (a factorial if the argument is integer). When *n* is reasonably large, the chi distribution is nearly the same as Normal distribution, with mean converging to $\sqrt{n-\frac{1}{2}}$ (Bland 2004), so $E\left(\chi_n\right)\approx\sqrt{n-\frac{1}{2}}$

Thus $V(s)=\sigma^2-\dfrac{\sigma^2}{n-1}E\left(\sqrt{\chi_{n-1}^2}\right)^2\approx\sigma^2-\dfrac{\sigma^2}{n-1}\left(\sqrt{n-1-\dfrac{1}{2}}\right)^2=\dfrac{\sigma^2}{2(n-1)}$

The appropriate weight for a WLS regression of speed standard errors using radar gun data is therefore approximately $(n-1)$.

Table 4-11 provides WLS estimation results for both models.

Five explanatory variables, including speed limit, were statistically significant in the final **average speed** model. Figure 4-3 presents a scatterplot of average speeds versus speed limits for all observations; a positive correlation clearly exists between these two variables. However, it can be seen from the estimation results that a change in speed limit is associated with a less than equivalent change in the average speed. For example, a 10 mi/h increase in speed limit is associated with a roughly 6.5 mi/h increase in average speed, other things equal. With respect to other explanatory variables, freeways (with more restricted access control) are estimated to exhibit an average speed 4 mi/h higher than uncontrolled access facilities, everything else constant. Wet pavement is predicted to reduce average speeds by about 3 mi/h. Higher flow rates and the presence of a downstream intersection within one-quarter mile both reduce the estimated average speed. (None of the sites had nearby upstream intersections, so the possible effects of these on speed averages or standard errors could not be analyzed.) The adjusted R2 measure of model fit is 0.64, which appears quite satisfactory but may be biased upwards since the least squares assumption of independent error terms is violated by the repeated observations.

Five statistically significant explanatory variables also remain in the final specification of the WLS regression model for **speed standard error**. Although the presence and coefficients of the significant explanatory variables all appear reasonable, the overall quality of model fit is minimal (R2 values under 0.02). Interestingly, the results suggest that a 10 mi/h increase in speed limit reduces the standard error of speeds, but only by 0.2 mi/h. Freeways and rural facilities exhibit higher speed variations, everything else constant. The presence of a nearby downstream intersection and a greater number of lanes are predicted to increase the standard error in observed speeds, as one may expect (due to behavioral shockwaves and additional flexibility in speed choice, respectively). Wet pavement and flow rates are predicted to have no statistically significant effect on speed variation. Finally, lighting conditions are insignificant in both models; this is likely because observations were made during daylight and dusk, but not at night.

Although the models developed here are somewhat limited by their reliance on a relatively small dataset collected in a single region during a single month, and by the fact that the analysis does not account for the panel nature of the data, these findings are still valuable because of their use of individual vehicle speed measurements, and helpful in providing a sense of how speed limits influence speed conditions on high-speed roads.

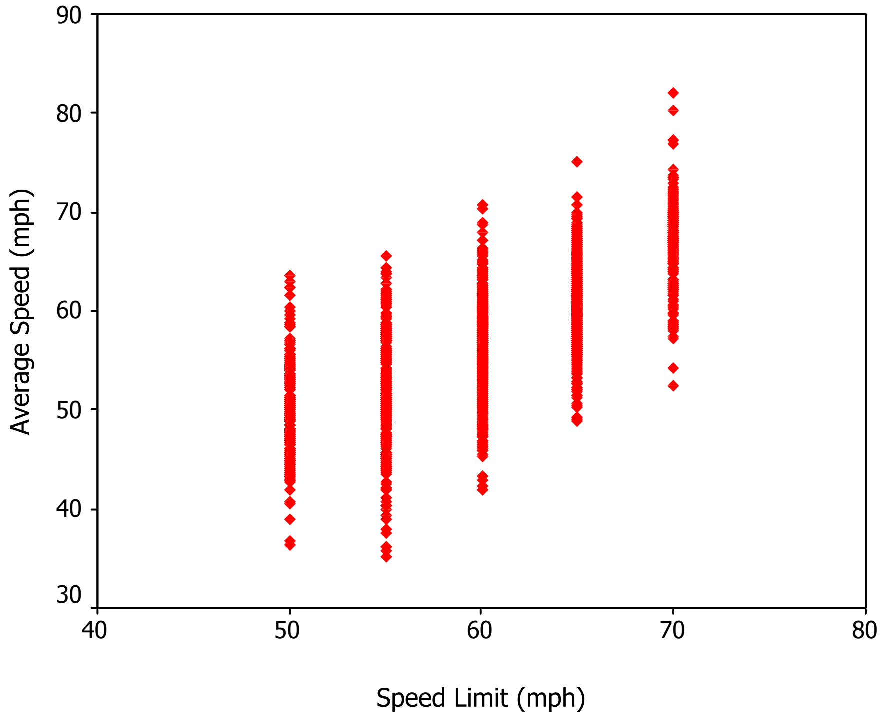

Figure 4-3 – Average Vehicle Speeds *vs.* Speed Limits in Austin, Texas

Table 4-10 – Summary Statistics for Austin Speed Data

Variable Name	Variable Description	Variable Statistics			
		Min	Max	Mean	Std. Dev.
INTERVAL	Detection interval (sec)	5	20	12.39	4.82
AVGSPD	Average speed observed during each interval (mi/h)	35.1	82	57.32	6.91
SPDVAR	Standard error of speeds during interval (mi/h)	0.55	14.98	4.24	1.82
DAYTIME	1 if observed during daylight; 0 at dusk	0	1	0.864	0.343
URBAN	1 if the section is in an urban area; 0 otherwise	0	1	0.339	0.474
DRY	1 if the pavement is dry; 0 otherwise	0	1	0.864	0.343
INTERSXN	1 if there is a downstream intersection within 0.25 mile; 0 otherwise	0	1	0.241	0.428
#LANES	Number of lanes total (in both directions)	4	8	5.403	1.600
FLOW	Equivalent hourly lane flow volume (veh/h/lane)	180	2880	1107	463.7
SPDLIMIT	Speed limit (mi/h)	50	70	60.43	6.061
FREEWAY	1 if the section is on a (controlled access) freeway; 0 if on a highway	0	1	0.581	0.494

Table 4-11 – WLS Model Results for Austin Speed Data

Variable	Y = Average Speed				Y = Speed Standard Error			
	Initial Model		Final Model		Initial Model		Final Model	
	coef.	t. stat.	coef.	t. stat.	coef.	t. stat.	coef.	t. stat.
(Constant)	14.606	9.54	15.196	12.05	5.455	8.21	4.703	8.67
DAYLIGHT	-0.252	-0.7	---	---	-0.175	-1.12	---	---
URBAN	0.442	1.01	---	---	-0.519	-2.74	-0.346	-2.44
DRY	2.841	8.96	2.702	10.45	-0.217	-1.58	---	---
INTERSXN	-2.386	-8.44	-2.369	-8.96	0.493	4.02	0.517	4.75
#LANES	-0.167	-1.36	---	---	0.17	3.19	0.118	2.78
FLOW	-9.92E-04	-4.07	-1.01E-03	-4.32	-9.58E-05	-0.91	---	---
SPDLIMIT	0.677	24.13	0.651	32.7	-3.08E-02	-2.53	-2.09E-02	-1.94
FREEWAY	3.547	10.8	3.793	16.08	0.418	2.93	0.295	2.36
R-sqrd.	0.646		0.645		0.018		0.016	
Adj. R-sqrd.	0.644		0.644		0.014		0.013	

Note: Nobs = 1,766; WLS weights = counts

4.2.4 Speed Limit Change Intervention Analysis in Washington State

Washington State is one of the nine states included in the Highway Safety Information System (HSIS), a multi-state database sponsored by the Federal Highway Administration that contains crash, roadway inventory and traffic volume information. States are selected to be part of the HSIS on the basis of the diversity, quantity and quality of the data that they regularly collect, and their ability to merge data of different types and disparate sources. Washington State became part of the HSIS in 1995.

In addition, Washington State DOT (WSDOT) operates an extensive set of permanent traffic recorders (PTRs), and maintains historical archives of detailed traffic data measurements from these stations.

These two factors made Washington State a particularly interesting source of crash-related data for project analyses.

4.2.4.1 Data Preparation

The project obtained WSDOT traffic data for areas outside of the northwest Washington region including Seattle from Jim Hawkins (in the State's Transportation Data Office, Highway Usage Branch) and his staff. Using crash milepost data, the 1996 HSIS crash observations were situated with respect to the state's 149 PTR locations[21] in order to identify a set of detector stations from which to request data. Since the WSDOT traffic data take significant time and effort for staff to assemble, the project wanted to limit its request to relevant stations.

Table 4-12 shows how many crashes can be linked to PTR stations within given distances of the crash site. Among the 42,141 crashes in the 1996 HSIS dataset, 23.4% (9,849 cases) occurred within 3 miles of a PTR, 17.2% occurred within 2 miles, 3.7% occurred within 1 mile and 5 % occurred within 0.5 mile of a PTR. Within each of four distance categories, about 45% are injury crashes and just 0.5% are fatal crashes. A 2-mile distance was chosen as the criterion to use in requesting PTR data because a 1-mile distance reduces the percentage of crash coverage by detectors from 17% to less than 4%.

Table 4-12 – Distribution of Crashes by Distance to Nearest WSDOT Detector Station

Distance (mi)	Injury Crashes / Fatal Crashes	All Crashes	Urban / Rural
3	4395 (44.6%)	9849 (23.4%)	8015 (81.4%)
	48 (0.5%)		1834 (18.6%)
2	3244 (44.8%)	7245 (17.2%)	5912 (81.6%)
	36 (0.5%)		1333 (18.4%)
1	1854 (45.4%)	4085 (3.7%)	3384 (82.8%)
	15 (0.4%)		701 (17.2%)
0.5	975 (46.5%)	2098 (5%)	1752 (83.5%)
	8 (0.4%)		346 (16.5%)

About 32% of the crashes in the 1996 HSIS occurred on "rural" roads; the remaining 68% occurred on "urban" roads.[22] About 8% of the crashes occurred on roads with a posted speed limit of 70 mi/h, just 1% on 65 mi/h roads, 26% on 60 mi/h roads and 15% on 55 mi/h roads; the remaining 52% occurred on roads with speed limits less than or equal to 50 mi/h.

In 1996, roughly 150 of the PTR directional stations had at least one crash within 2 miles, but 12 of these stations were located on roads with speed limits under 50 mi/h and thus were not suitable for the purposes of this study. Among the remaining 138 stations, 54% were on rural roads and 46% were on roads with a 60 mi/h speed limit; 34% of the stations were on urban roads with a 60 mi/h speed limit. Although many rural sites seem to be represented, those with the most injury crashes tend to be urban. For example, among the 50 stations associated with the highest number of injury crashes, only two are on rural roads. This is due to the high traffic volumes that urban roads carry, not necessarily because they are more dangerous.

Based on this examination, the project requested and obtained data for six of the 149 PTR stations:

[21] 101 of these are classification sites, and 48 are weigh-in-motion (WIM) sites. When one considers that separate directions on divided highways act as distinct stations (e.g., stations R047W and R407E for west and east directions of flow), there are 163 total stations.

[22] WSDOT traffic detector data files do not distinguish urban or rural road type. The station classification comes from matching those sites with the HSIS dataset's urban/rural classification of Washington mileposts.

- P4N&S, which is at Boulevard Road in Olympia, in the Puget Sound region;
- P06, which is in Camas, in the southwest region of the state;
- D1N&S, which is at 112th Avenue in Bellevue in the Puget Sound region;
- D10, which is near 76th Avenue in the Puget Sound region;
- P10, which is in Ritzville, in the eastern region of the state; and
- P03, which is in Wapato, in the south central region of the state.

Additional characteristics of these sites are provided in Table 4-13, and their locations are shown in Figure 4-4. The PTR records for these stations were obtained for a data period covering the three complete calendar years of 1995, 1996 and 1997. This period spans the date of the NMSL repeal in Washington State on March 16, 1996.

Table 4-13 – Site Characteristics of Six WSDOT Traffic Detector Stations

PTR* Number	Route Num.	Milepost	Urban/Rural	Pre-Speed Limit	Post-Speed Limit
P4N&S	5**	106.7	Urban	55	60
P06	14	11.9	Urban	55	55
D1N&S	405**	9.26	Urban	55	60
D10	520	4.0	Urban	50	50
P10	90**	218.83	Rural	65	70
P03	97	66.3	Rural	55	55

* Permanent Traffic Recorder
** Indicates an interstate highway.

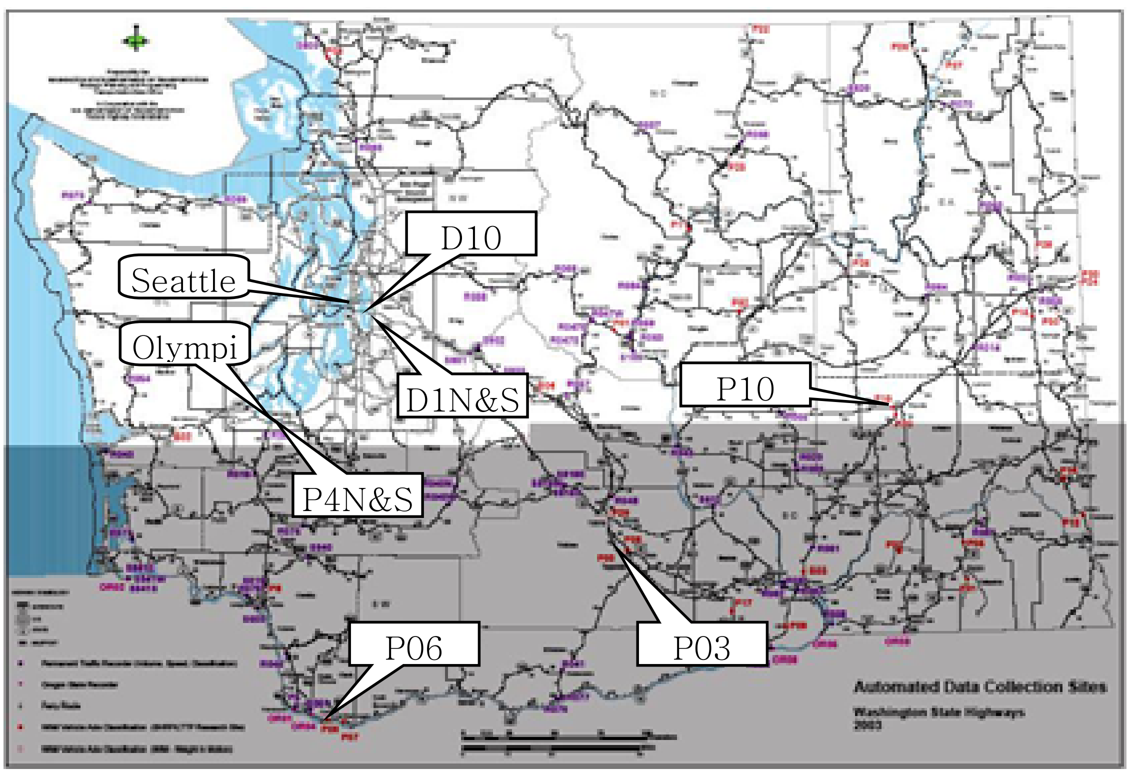

Figure 4-4 – WSDOT Detector Stations Providing Data for the Analysis

The resulting dataset consisted of speed and traffic volume data for the four stations, in a day-by-day time-series format, over the three-year data period. These data are summarized in the following table.

Table 4-14 – Summary Speed Data Statistics at Four Washington Detector Stations

Site	Variable	Mean	Std. Dev.	Min.	Max.
P03 Northbound	Average Speed (mi/h)	56.53	2.50	29.77	63.74
	Speed Variance (mi^2/h^2)	27.86	17.78	17.80	255.17
P03 Southbound	Average Speed	56.01	1.91	40.54	61.35
	Speed Variance	34.76	18.46	21.51	251.42
P4N Northbound	Average Speed	58.03	1.45	50.23	61.80
	Speed Variance	22.21	6.16	16.60	108.14
P4S Southbound	Average Speed	58.02	1.58	37.44	61.80
	Speed Variance	22.50	9.29	16.60	206.82
P06 Eastbound	Average Speed	56.38	1.09	41.22	58.30
	Speed Variance	23.08	7.20	18.38	186.38
P06 Westbound	Average Speed	60.24	1.11	44.90	61.90
	Speed Variance	25.82	5.71	21.41	144.28
P10 Eastbound	Average Speed	67.02	1.97	55.26	70.83
	Speed Variance	32.28	8.76	20.55	113.24
P10 Westbound	Average Speed	67.93	2.04	53.35	71.88
	Speed Variance	34.70	8.95	1.37	119.88

4.2.4.2 Model Estimation and Analysis

A before-after study based on a statistical test of differences in averages, such as Student's t test, might seem to be an appropriate approach to analyze these data. However, the presence of serial correlations, non-stationarity and seasonality in the observations is likely to invalidate the results of this or similar elementary statistical tests, which are generally based on an assumption of independent observations (Box and Tiao, 1975).

For this reason, the project decided to analyze the data using time-series intervention analysis (known as ARIMA[23] intervention analysis), recognizing the speed limit change as an intervening event. The pre-intervention period for this study was defined to be the portion of the data period prior to the speed limit change. It thus covered the period from January 1, 1995 through March 15, 1996, and contained 439 days of traffic data. The post-intervention period was March 16, 1996 though December 31, 1997, and contained 656 days of data. On average, 12% of the 1095 observations (days) were missing due to detector malfunctions[24] (with a range of 9 to 16 %); these data were treated as "missing" in the estimation.

[23] ARIMA is an acronym for **a**uto-**r**egressive **i**ntegrated **m**oving **a**verage.

[24] A detector was considered to be malfunctioning if a volume of zero was recorded for an entire day, or if a particular date was entirely missing from the raw data records.

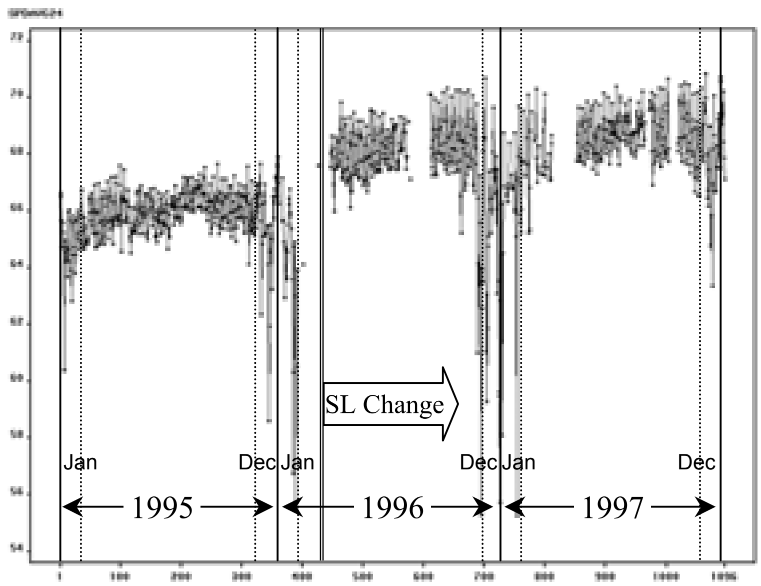

Figure 4-5 – Eastbound Average Speed at the P10 station in 1995-1997

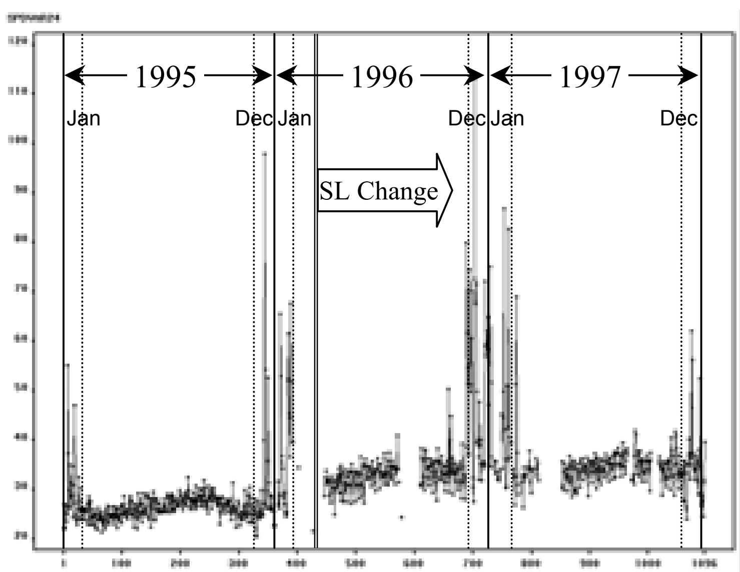

Figure 4-6 – Eastbound Speed Variance at the P10 station in 1995-1997

The key assumption in this intervention analysis is that the ARIMA process that characterizes the pre-intervention series remains unchanged in the post-intervention period, so that any observed change can validly be attributed to the intervention (Yaffee and McGee, 2000). However, even a quick examination of the data reveals them to be non-stationary. For example, the average speed and speed variability at station P10 (shown in Figure 4-5 and Figure 4-6) tend to increase with time. Transforming the data by computing differences between successive values may render them more nearly stationary. Moreover, the data appear to exhibit strong seasonality since, for example, variations in average speed and speed variance are clearly more substantial during the winter. Therefore, seasonal differencing (e.g., differencing every 365th pair of observation values) may also be needed. Both approaches were examined, as described below.

To account for an intervention, ARIMA intervention analysis adds an impulse function to the basic ARIMA process. The characteristics of the impulse function reflect those of the intervention's effect (e.g., its duration and nature of onset), where *a priori* reasoning or visual examination of the data can sometimes suggest a functional form to represent these effects. Step functions (for a permanent effect) and pulse functions (for a temporary effect) are two commonly used forms (Box *et al*., 1994).

Since the speed limit was raised at two of these four sites on March 16, 1996 and the higher limit remained in effect until the end of the data period, a permanent intervention effect was assumed and a step response function was applied to represent it. This was accomplished by including in the model an indicator variable for speed limit change.

Examination of a dataset's autocorrelation function (ACF) and partial ACF (PACF) can sometimes suggest appropriate values for the *p*, *d* and *q* parameters of the ARIMA process' autoregressive (AR), integrating (I) and moving average (MA) components, respectively. However, for these particular data the ACF and PACF failed to suggest clear *p*, *d* or *q* parameter values, so all of the standard ARIMA specifications (with p=0, 1, and 2, d=0 and 1, and q=0, 1, and 2) were estimated. Seasonal differencing with several values around 365 was also attempted, but did not perform well. . All ARIMA estimations were performed using the SAS system software.

Diagnostics were performed on all estimated models. At each station and direction, several models generally appeared to be appropriate and similar to one another in their performance, so that it was difficult to distinguish a single "best" model for each case. However, the estimates of the speed limit change effects were similar in all cases, so the range of values estimated in the various models are provided in Table 4-15 below.

Table 4-15 – ARIMA Model Estimates of Effect of Speed Limit Change on Speed Average and Variance

PTR Number	Urban/ Rural	Limit Change	Direction	Effect on Speed Average (mi/h)	Effect on Speed Variance (mi^2/h^2)
P03	Rural	0	Northbound	–*	-10.782
			Southbound	–	-15.314
P10	Rural	+ 5 mi/h	Eastbound	1.594	5.056
			Westbound	1.241	5.671
P06	Urban	0	Eastbound	0.783	–
			Westbound	0.447	–
P4N&S	Urban	+ 5 mi/h	Northbound	1.227	-
			Southbound	1.312	-

* '–' indicates no statistically significant effects.

Note: All values are statistically significant at the 0.05 significance level (and most are significant at the 0.001 level). R-squared values are in parentheses.

Considering the two sites that experienced 5 mi/h speed limit increases, average speed there increased by amounts ranging from roughly 1.2 to 1.6 mi/h. Speed variance increased by about 5 mi^2/h^2 at the rural site (PTR P10); on the other hand, no statistically significant effect of the speed limit change on speed variance was found at the urban site (PTR P4N&S).

In contrast, the two stations (PTR P03 and P06) that did not experience speed limit changes exhibited virtually no changes in average speed and speed variance at the time of the speed limit change. The urban site whose limit was unchanged (PTR P06) may have experienced a slight spillover effect, in which its average speed increased as a result of speed limit increases at other sites, but this was on the order of just 0.6 mi/h. It is possible that urban locations are more prone to speed limit change spillover effects due to their denser networks, which provide more trip routing options and more opportunities to use multiple highways in a single trip. Thus, urban-area drivers may become more accustomed to the higher speed limits and drive similarly on other highways whose limits have not changed. However, the effect seems slight.

Along with the ARIMA intervention models, simple linear regression models with linear time trend variables and an indicator variable for the speed limit change were also specified and estimated using ordinary least squares (OLS). The results are presented in Table 4-16. Although all estimated values appear to be statistically significant at the 0.05 significance level, their standard errors are biased downward, so their actual significance is less than indicated. While some of the estimates are similar to the results of the time series models, they are generally lower in value. Moreover, the estimated effects on speed variances at the PTR P03 site appear quite unreasonable (-10.8 mi^2/h^2 and -15.3 mi^2/h^2 in the northbound and southbound directions, respectively, at a site where no speed limit change took place). Of course, an OLS approach neglects the serial correlation in the data, resulting in inefficient estimators and biased estimates of their standard errors. For these reasons the results of the ARIMA intervention analysis are preferred.

Table 4-16 – OLS Model Estimates of Effect of Speed Limit Change on Speed Average and Variance

PTR Number	Urban/ Rural	Limit Change	Direction	Estimated Effect on Speed Average	Estimated Effect on Speed Variance
P03	Rural	0	Northbound	–	-10.8
			Southbound	–	-15.3
P10	Rural	+5 mi/h	Eastbound	1.59	5.1
			Westbound	1.24	5.7
P06	Urban	0	Eastbound	0.78	–
			Westbound	0.45	–
P4N&S	Urban	+5 mi/h	Northbound	1.23	–
			Southbound	1.31	–

In addition to OLS and ARIMA regression models, simple before-after statistical comparisons of the Washington State PTR data were performed. The project conducted t-tests of differences in means with heteroscedastic variance to compare average speeds, and F-tests to compare speed variances. The results suggested that all sites experienced statistically significant changes (at the 0.001 significance level) in both their speed average and speed variance. However, the estimated effects are small in value, ranging from 0.6 to 2.4 mi/h for average speeds, and from -0.5 to +2.0 mi^2/h^2 for speed variances. As noted above, these statistical tests assume independent observations, which is not the case here due to serial autocorrelation. Thus, the ARIMA results remain preferred.

In summary, a variety of time-series model results for four distinct highway sites in the State of Washington suggest that those sites experiencing speed limit changes exhibited increases in their average speeds and speed variances, while those without such changes exhibited practically no change. The increase in observed average speeds was just 2 mi/h for a 5 mi/h speed limit change. The rural site experiencing a speed limit change appeared to be more affected than the urban site experiencing a change. This latter conclusion may apply more generally to other sites, particularly if congestion in urban area imposes limits to chosen speeds and their variation.

4.2.5 Analysis of Rational Speed Choice Using Simulated Data

In addition to the empirical analyses of actual speed data, a theoretical model of how rational drivers choose their driving speeds was also developed. This work is described here.

It is reasonable to hypothesize that a driver chooses his or her speed to minimize a generalized cost of travel. In this context, the generalized cost consists of travel time costs, crash costs, legal costs (from traffic fines if caught speeding) and vehicle operating costs. All of these cost components depend, to some extent, on the chosen speed. McFarland and Chui (1987) made a similar hypothesis, in an attempt to estimate the value of travel time using telephone interview survey data (along with numeric assumptions drawn from previous studies).

Since the speed-related contribution of vehicle operating costs can be expected to be rather negligible compared to the other three costs,[25] it was decided to exclude that component from additional consideration.

Several functional forms were considered for each of the cost components. For crash and legal costs, linear, quadratic, and logit specifications were considered. The quadratic form was chosen because it is simple to handle yet reasonably accommodates non-linear relationships, particularly when the domain is limited. The following is the final minimization formulation that was specified by the study:

$$\min_{Speed} TC(Speed) + CC(Speed) + LC(Speed)$$

where
$$\begin{aligned}
TC(Speed) &= b_0^t + b_1^t \times Wage \times Speed^{-1} \\
CC(Speed) &= [b_0^c + b_1^c \times |Speed - SSPD| + b_2^c \times |Speed - SSPD|^2] \\
&\quad \times [a_0^c + a_1^c \times (Speed - SSPD)^2], \\
LC(Speed) &= [b_0^l + b_1^l \times (Speed - SL) + b_2^l \times (Speed - SL)^2] \\
&\quad \times [a_0^l + a_1^l \times (Speed - SL)] \times \mathbf{I}(Speed > SL).
\end{aligned}$$

[25] According to equations for operating costs of medium passenger cars in 1982 (McFarland and Chui, 1987), vehicle operating costs increase roughly 0.13 and 0.23 cents per mile driven per mile per hour, when speeds rise from 50 to 60 mi/h and from 60 to 70 mi/h, respectively. Reed (2001) also chose to exclude vehicle operating costs from his analysis, for the same reason.

Here t indexes travel time cost parameters, c indexes crash cost parameters, l indexes legal cost parameters, i indexes an individual driver, TC is a travel time cost, CC is a crash cost, LC is a legal cost associated with speeding, $Wage$ is an hourly wage, $SSPD$ is the safest speed, SL is the speed limit and $\mathbf{I}(\cdot)$ is an indicator function (equaling 1 if the parenthesized condition is true and zero otherwise). The safest speed ($SSPD$) was treated as exogenous; it was viewed as a design speed for straight highway sections, potentially ranging from 70 to 120 mi/h[26] and corresponding to 55 to 75 mi/h speed limits. (An extension of this approach might estimate it as a function of geometric design and other variables.)

This specification is an unconstrained non-linear minimization problem. One standard approach for solving such problems is to derive a system of equations based on the problem's optimality conditions, and to solve these; the roots of the equation system are candidate solutions of the original optimization problem. In this case, the equation derived from the first-order necessary condition with respect to $Speed$ is:

$$
\begin{aligned}
&\frac{\partial(obj\ fxn)}{\partial Speed} = 0; \\
&-b_1^t \times \frac{Wage}{Speed^2} + 100\left[b_1^l + 2b_2^l(Speed - SL)\right] \times \left[a_0^l + a_1^l(Speed - SL)\right] \\
&\times \mathbf{I}(Speed > SL) + 100\left[b_0^l + b_1^l(Speed - SL) + b_2^l(Speed - SL)^2\right] \\
&\times a_1^l \mathbf{I}(Speed > SL) + 100\left[b_0^l + b_1^l(Speed - SL) + b_2^l(Speed - SL)^2\right] \\
&\times \left[a_0^l + a_1^l(Speed - SL)\right] \times \left[\frac{\partial}{\partial Speed}\mathbf{I}(Speed > SL)\right] \\
&+ \left[-b_1^c \frac{\partial}{\partial Speed}\left|Speed - SSPD\right| - 2b_2^c\left|Speed - SSPD\right| \frac{\partial}{\partial Speed}\left|Speed - SSPD\right|\right] \\
&\times \left[r_0^c + r_1^c(Speed - SSPD)^2\right] + 2\left[b_0^c + b_1^c\left|Speed - SSPD\right| + b_2^c\left|Speed - SSPD\right|^2\right] \\
&\times r_1^c(Speed - SSPD) = 0
\end{aligned}
$$

Second-order sufficient conditions ensure that a solution of this equation also minimizes the objective function of the minimization problem. Unfortunately, a closed form analytical solution of this equation could not be obtained, either by hand or using the MAPLE 8 symbolic mathematics system by Maplesoft.

In order to advance farther in this analysis of rational speed choice, a different approach was pursued. Rather than trying to solve the optimization problem for any arbitrary values of the various coefficients and variables, synthetic datasets were generated in which each record consisted of specific values for each of the parameters and variables used in the model. The data generation process involved both deterministic and random number generation, and ensured that a reasonable range of values for each parameter and variable was covered: the range of parameter values was compared to a range of estimates found in past studies.

[26] Very high "safe speeds" (up to 120 mi/h) are potentially possible on straight segments, where sight distances may be great (under lighted conditions) and centrifugal forces are not present.

Two large datasets were generated in this way. (Appendix D provides more details regarding the generation and characteristics of these synthetic datasets.) The MATLAB mathematical software package (MathWorks Inc. 1992) was then used to numerically find the optimal speed corresponding to each specific set of parameter and variable values. After the results were checked for validity and reasonableness, a statistical analysis was conducted of the relationship between the optimal speeds that were developed from this procedure and the key explanatory variables.

Table 4-17 presents estimates of linear models of optimal speed as a function of some of the key explanatory variables, estimated from the two sets of generated data. Both regressions result in very high R-squared values (0.97 and 0.98), and the estimated coefficients are all significant as well as consistent across the two models. The estimated coefficients of speed limit variables are within reasonable bounds according to empirical findings of past studies: past studies suggest that speed changes are less than speed limit changes, and often less than half of the speed limit changes (e.g. Ossiander and Cummings 2002; Jernigan and Lynn 1991; Upchurch 1989).

Although the results of Table 4-17 do not originate from empirical data, they do suggest that a simple linear specification for speed choice may serve well in predicting choices that emerge from highly complicated choice processes. Moreover, if the assumed parameter values are reasonably realistic, these results suggest that safe speeds, for which design speeds may be a good proxy, are more important in determining actual speed choice than are speed limits: the coefficients on SSPD exceed those on SL by 25% to 80%. While the coefficients of these two explanatory variables differ, they do appear to *complement* one another in a dramatic way: an increment of 1 mi/h in *both* these speeds is predicted to result in an almost 1.0 mi/h increase in chosen speed. This result is quite interesting and reasonable and, at the same time, is not obvious from the model specification.

The results also suggest that wage may have a relatively minor effect; however, the predicted magnitude (roughly 0.1 mi/h for every $100 change in hourly wage) seems unrealistically small.

Table 4-17 – Linear Regression Model of Simulated Rational Speed Choice

Dataset	Dataset 1			Dataset 2		
Variables	Coef.	Std. Err.	t-stat	Coef.	Std. Err.	t-stat
Constant	-3.1001	0.025421	-121.949	-3.4503	0.011746	-293.750
WAGE	0.001004	0.000175	5.743	0.0007099	8.73E-05	8.135
SSPD	0.5525	0.000143	3870.436	0.6235	6.6E-05	9448.173
SL	0.4422	0.000324	1366.037	0.3735	0.00015	2495.995
Nobs.	495,000			1,856,250		
R-sqrd.	0.972			0.981		
Adj. R-sqrd.	0.972			0.981		

4.3 Crash Occurrence Models

This section describes the project's analyses of crash occurrence models. Crash occurrence is quantified in a number of different ways in these analyses: in some cases as crash counts and in others as crash rates with respect to VMT. Similarly, some models consider all crashes regardless of severity, while others investigate crashes by type or severity. The work relied heavily on HSIS data for Washington State; these data were complemented by information from other sources. As will be seen, some analyses made use of the HSIS data in their original (i.e. disaggregate) form; however, analyses using aggregated forms of the HSIS data proved much more productive.

The following analyses are described below:

- A model of crash occurrence based on a panel dataset of clustered HSIS data for Washington State (section 4.3.1); and
- A before-after model of crash occurrence changes based on clustered HSIS data (section 4.3.2).

Again, the project performed additional analyses of crash occurrence models that, for a variety of reasons, were not considered to give satisfactory results. Discussions of these analyses are included for completeness, but have been relegated to the appendices. The analyses include:

- A model of crash occurrence based on segment-level (unclustered) HSIS data for Washington State (Appendix F);
- A simple exploratory analysis of speed limit change impacts using the segment-level HSIS data (Appendix G);

4.3.1 Crash Occurrence Models Using Clustered HSIS Panel Data

HSIS data concern short homogeneous roadway segments and so are highly disaggregate. While disaggregate data can be advantageous for some purposes, crash data on disaggregate roadway segments tends to consist of many observations with zero or a low number of crashes, and this characteristic of the data conflicts with the assumptions of many "conventional" statistical methods and analyses.

Accordingly, it was decided to convert these same data into a more aggregate form using data clustering procedures. These procedures combine a large number of disaggregate data points into a much smaller number of clusters, where each cluster groups together a set of data points that are in some sense similar to each other and different from the points belonging to other clusters. Attributes of the cluster are computed from the attributes of the data points that belong to it. Aggregation makes the resulting dataset more suitable for statistical analyses such as least squares regression and its generalizations.

4.3.1.1 Data Preparation

The crash datasets used in this analysis were collected from Washington State through the Highway Safety Information System (HSIS). The HSIS data contain information on vehicle occupants' demographics, roadway design features including speed limits;[27] vehicle characteristics; environmental conditions at the time of crash; and basic crash information such as crash severity, time, location and type.

HSIS data were extracted for the years 1993 through 1996 and 1999 through 2002, which bracket the repeal of the National Maximum Speed Limit.[28] The HSIS indicates that a total of more than 760,000 vehicle occupants were involved in 263,970 reported crashes, resulting in more than 2,400 fatalities on Washington State highways in this period.

Because of the project's focus on high-speed roads, any straight segments having speed limits less than 50 mi/h were excluded from the dataset. However, curved sections with speed limits less than 50 mi/h on otherwise high-speed roads were retained in the dataset in order to increase the variability in the independent variables.

Rather than analyzing individual crashes and the factors associated with their occurrence, the approach here was to define clusters of roadway segments with relatively homogeneous characteristics, and to relate the clusters' aggregate crash performance to their characteristics. Clustering was originally performed using statistical procedures that automatically group a set of observations into clusters by minimizing some measure of dispersion of the variables of interest within clusters, and maximizing the dispersion between clusters. However, the clusters that resulted from this procedure had no intuitive interpretation, so it was decided to define clusters manually, in terms of meaningful and reasonable thresholds for the variables of interest. Regardless of the clustering procedure, cluster analysis eliminates some of the discreteness and variability in the data, and may allow the use of simpler statistical techniques.

Segments were assigned to clusters based on their design attributes (number of lanes, roadway classification, terrain, presence of median, degree of curvature, vertical grade, and right shoulder width).[29] Threshold values of each variable used for clustering are shown in Table 4-18.

[27] The HSIS speed limit information is routinely provided off cycle from the other data, so correct speed limit information was obtained from Washington DOT's Bob Howden.
[28] Data for 1997 and 1998 were not available because complete HSIS data records for those years were unfortunately not kept.
[29] AADT per lane also is an important variable that may be of value for clustering (so that high-demand roadways are not grouped with low-demand roadways). However, it is far from certain that a panel of clustered segments would remain stable in this attribute over time. Therefore, this variable was not used for clustering purposes here.

Table 4-18 – Variable Thresholds for Cluster Definitions in the Crash Count Model

Variable	Thresholds	#groups
# lanes	2 & 3; 4 & 5; 6,7 & 8 lanes	3
Presence of median	yes/no	2
Rural location	yes/no	2
Interstate highway	yes/no	2
Terrain type	level; rolling; mountainous	3
Non-interstate freeway	yes/no	2
Degree of curvature (DC)	DC=0°; 0°<DC≤10°; DC>10°	3
Right shoulder width (RSW)	RSW=0; 0<RSW≤20; RSW>20 ft	3
Vertical grade (VG)	VG=0; 0<VG≤5; VG>5 %	3
Total possible clusters	3×2×2×2×3×2×3×3×3=3,888	

Since the intent was to isolate the effect of speed limit, roadway segments that experienced design changes affecting any of the cluster definition features during the period 1993-2002 were removed from the dataset. Out of 100,457 total segments in the base year (1998), 41,348 met the requirements of unchanged design features[30] through 2002. These observations account for 59% of total miles, 65% of VMT and 63% of total crashes.

Aggregate cluster crash counts and VMT were computed by summing the corresponding values of the included segments. Resulting totals were divided to create aggregate cluster crash rates. Aggregate values of explanatory variables were computed from the corresponding variable values of the included segments, weighing the individual values by the corresponding segment VMT. These calculations were performed on the data for each year of the analysis period.

The clustering procedure was applied based on segment attributes in 1993. The resulting cluster membership of each segment was maintained and applied to the segment observations for subsequent years, from 1994 through 1996 and from 1999 through 2002. Aggregate cluster attributes were computed for each year. The result is a panel dataset of segment clusters.

Summary statistics for the cluster dataset are shown in Table 4-19. Before clustering, there were 41,348 segments, the average crash count was 0.24 crashes (per year per segment), and the average segment length was just 0.09 miles. The clustering process created 337 clusters for each year, resulting in average crash counts of 26 crashes (per year per cluster) and average segment lengths of 10 miles (per cluster). The average VMT per lane was 283,654 vehicle-miles (per year per segment) before clustering, and rose to 31,033,070 after clustering.

Clearly, clustering makes the data much more continuous in nature, thus permitting application of more standard – and easier to interpret – linear models.

[30] The original intent was to include all relevant HSIS segments. However, since segments are homogeneous by definition, a change in a segment's attributes during the data period would cause it to be split into a series of shorter segments, and this caused problems matching segments in different years. The project attempted to create a fixed set of segments based on all attribute changes that occurred over the data period. Unfortunately, this still could not guarantee the correct identification of matching segments because of roadway realignments and data recording errors. It was therefore decided to use only those segments having attributes that remained unchanged over the entire period. By the same logic, it was also decided to remove any segments showing a purported speed limit increase of 20 mi/h or more, since these were most likely to be incorrect records. A total of 2,876 such segments were removed from further analysis.

Table 4-19 – Summary Statistics of Variables for 337 Segment Clusters Over Eight Years

Variable	Mean	Std. Dev.	Min	Max
Dependent Variables				
Number of total crashes	26.02	90.54	0	1469
Number of PDO crashes	14.32	50.32	0	799
Number of injury crashes	11.35	41.78	0	656
Number of fatal crashes	0.354	1.598	0	29
Number of occupants injured	18.41	69.67	0	1112
Number of occupants killed	0.4013	1.789	0	34
Independent Variables				
Segment length (miles)	9.975	56.12	0.05	931.8
Degree of curvature (°/100ft)	1.728	3.415	0	20.32
Vertical grade (%)	2.236	2.237	0	10
Total right shoulder width	9.678	9.189	0	50
Posted speed limit	55.19	8.326	25	70
AADT per lane	5949	3796	509	21470
Indicator for interstate highway	0.2404	0.4274	0	1
Indicator for non-interstate freeway	0.3531	0.4780	0	1
Indicator for presence of median	0.5608	0.4964	0	1
Indicator for rolling terrain	0.4748	0.4995	0	1
Indicator for mountainous terrain	0.1780	0.3826	0	1
Indicator for rural	0.5312	0.4991	0	1
Indicator for 2 or 3 lane highway	0.4006	0.4901	0	1
Indicator for 4 or 5 highway	0.4481	0.4974	0	1
Indicators for years 1994 – 2002				
Nobs. = 2,960 (337 clusters x 8 data years)				

4.3.1.2 Model Specification

Panel datasets, such as the one described above, offer a number of advantages compared to less structured data. Panel data permit identification of variations across individual roadway segments and over time. Accommodation of observation-specific effects also mitigates omitted-variables bias, by implicitly recognizing segment-specific attributes that may be correlated with explanatory variables. However, models that are applied to analyze such datasets must take account of their panel nature. Two of the standard model types that are appropriate for panel data are fixed and random effects models.

The specification of the fixed effects (FE) linear model is as follows (Greene 2002):

$$y_{it} = x_{it}'\beta + \alpha_i + \varepsilon_{it} \qquad \text{for } i = 1,2,\cdots,N \text{ and } t = 1,2,\cdots,T \tag{1}$$

where α_i is the fixed effect specific to roadway segment *i*, and ε_{it} is an error term that varies across both segments and time periods. The fixed effect α_i is a constant term that is determined separately for each segment and does not vary over time; its value can be estimated using the following formula (Greene 2002):

$$\alpha_i = \bar{y}_i - \hat{\beta}'_{\mathrm{FE}} \bar{x}_i \tag{2}$$

where $\bar{y}_i$ is the average response variable value for segment i (number of crashes, in this case) over the T time periods, $\bar{x}_i$ is the vector of average values of the explanatory variables for segment i over the T time periods, and $\hat{\beta}'_{\mathrm{FE}}$ is the least squares dummy variable (LSDV) estimator.

The specification of a random effects (RE) linear model is as follows (Greene 2002):

$$y_{it} = x'_{it}\beta + u_i + \varepsilon_{it} \tag{3}$$

where u_i is the random effect specific to roadway segment i, and other variables are defined as above. There is one random effect for each segment and it remains constant over time; however, each segment's individual u_i is assumed to be a realization from an underlying distribution of effects that is common to all segments.

Linear fixed effects models can be estimated using a least squares dummy variable (LSDV) model. Linear random effects models can be estimated using a generalized least squares (GLS) approach, by assuming an appropriate distribution for the random effects. Usually, RE estimates are more efficient than FE estimates since they are obtained by making use of both within-group and between-group variations (rather than only within-group variations). However, when there is correlation between omitted unobserved variables and included explanatory variables, the RE estimates become biased while the FE estimates remain unbiased (Hsiao, 2003).

The question arises as to which model should be used in practice. If FE models are used, there will be a loss of $N-1$ degrees of freedom in estimating the segment-specific effects. If RE models are used, it must be assumed that the segment-specific effects are uncorrelated with other, included variables. The Hausman test for such correlation can be performed using the following chi-squared statistic (Greene 2002):

$$W = \chi^2[K-1] = \left[\hat{\beta}'_{FE} - \hat{\beta}_{RE}\right]' \hat{\psi}^{-1} \left[\hat{\beta}'_{FE} - \hat{\beta}_{RE}\right] \tag{4}$$

where $\psi = Var\left[\hat{\beta}'_{FE} - \hat{\beta}_{RE}\right] = Var\left[\hat{\beta}'_{FE}\right] - Var\left[\hat{\beta}_{RE}\right]$ (5)

where $\hat{\beta}'_{FE}$ is the LSDV estimator for the FE panel model, and $\hat{\beta}_{RE}$ is the GLS estimator for the RE panel model. Greene (2002) notes that Hausman's assumption for calculating ψ is that the covariance of a random effect estimator and its difference from a fixed effect estimator is zero.

Hsiao (2003) argues that an FE model is more appropriate when the intent is to infer results for individuals in the sample, while an RE model is preferred for inferences relating to the larger population. However, in practice the choice of specification generally depends more on whether correlations exist between omitted variables and the included explanatory variables. Both the FE and RE model forms were estimated here, and Hausman's test was applied to evaluate the possibility of error-term correlation with explanatory variables.

4.3.1.3 Model Estimation and Analysis

A model of crash rates *vs.* traffic intensity would involve the *VMT* variable (the product of segment length and WSDOT AADT estimates for each segment) on both sides of the equation (in the denominator of the crash rate variable and in the numerator of traffic intensity/density variable). Since this can create spurious correlations, the *VMT* variable was moved to the right-hand side of the model specification, interacting it with the other explanatory variables. As a result, crash count (rather than rate) is the dependent variable:

$$Count_{it} = VMT_{it} \times \left(\beta X_{it}\right) + \varepsilon_{it} \tag{6}$$

where $Count$ refers to crash count (number of crashes per year per segment), and the *X's* are variables such as speed limit, degree of curvature, lane-use density (AADT per lane), right shoulder width, presence of median, vertical grade, and indicators of roadway classification and rural location, as well as a constant term.

Both FE and RE linear models were estimated for total crashes. Hausman test results suggested that there was no significant correlation between the RE model random error terms and the included variables, so the RE estimates were preferred here for reasons of statistical efficiency. Furthermore, the RE models are preferred because most of design features are time invariant, and thus cannot be estimated using FE models. The final estimation results for the RE model are shown in Table 4-20. The R-squared goodness of fit statistic suggested that 96% of the variation in crash count occurrence was accounted for by the model's explanatory variables.[31]

In interpreting this table, it is important to note that, although VMT was interacted with all of the variables shown in the model specification, the coefficient estimates shown in the table have *not* been multiplied by VMT. Consequently, the reported values are estimates of the crash *rate* coefficients. In order to interpret the results in terms of their crash *count* implications, the coefficients must be multiplied by VMT.

The effect of a speed limit change on overall crash frequency can be directly estimated from these results. As can be seen from the standardized coefficients in Table 4-20, speed limit is an important factor that positively impacts crash frequency. However, the presence of the squared speed limit with a negative coefficient moderates the simple linear effect to some extent. The combination of these two terms implies that 3.29% more crashes would be expected if speed limits were to increase 10 mi/h (from 55 mi/h to 65 mi/h), when all other control variables are

[31] The R-squared is quite high, thanks in large part to the inclusion of a "size" term (VMT) on the right-hand side of the equation. If crash counts were normalized with respect to this size term, the dependent variable would become a crash rate, and the regression of the segments' crash rates on all other control variables would result in an R-squared of 0.18.

held at their average values.[32] Very roughly, this model suggests that a 10 mi/h speed limit increase is associated with a 3% increase in overall crash frequency.

Holding all factors fixed (including roadway design and traffic intensity), the relationship between total crash rate and speed limit is concave, with a maximum around 73 mi/h. Because of the quadratic specification, the curve eventually falls, but extrapolation beyond 70 mi/h goes outside the range of observed data and is not credible.

The results of Table 4-20 also suggest that roadway design plays an important role in predicting crash occurrence. For example, more crashes are expected on sharper horizontal curves as well as on steeper vertical curves. Crash rates are also predicted to rise with increasing traffic intensity (measured as AADT per lane). This is probably due to the greater interaction among vehicles that occurs under more congested conditions. The presence of a median also significantly reduces crash frequency.

Table 4-21 defines three example segments that were used to investigate the model's predictions regarding speed limits and crash rates. The three segments are drawn from clusters with relatively low, medium and high speeds, respectively, and have attributes that are typical for the cluster. All are tangent sections on non-interstate highways, in 1993, with respective speed limits of 45, 50, and 55 mi/h. Table 4-21 provides additional details on the characteristics of these segments.

The model was applied to predict the crash rate effects of speed limit increases of up to 15 mi/h from the segments' original speeds. Figure 4-7 provides a graphical summary of these predictions. It can be seen that the predicted relationship is slightly concave: crash rates rise with increasing speed limit, but at a decreasing rate. The figure gives a sense of the overall magnitude and shape of the predicted effect of speed limits on crash rates. As can be seen, the effect is not dramatic, but it is practically and statistically significant. Note that, because of the concavity of the relationship, the magnitude of the effect tapers off at higher speeds.

A summary of results for speed limit and all other control variables is presented following the discussion of crash severity models, in Table 4-26. This table allows one to appreciate the effects of various design and use variables on crash severity as well as crash frequency. Note that these conclusions apply only to the sample sections considered here, and should not be interpreted to apply to other roadways in other circumstances.

[32] In this context, an average roadway section refers to a section with 2°/100ft degree of curvature, 2% vertical grade, on a four-lane divided rural interstate highway, with 10 ft shoulder width, and carrying 6,000 AADT per lane and 31,033,070 VMT in the year 1996.

Table 4-20 – Linear Random Effects Models of Crash Counts

Variables \ Models	Initial Model			Final Model		
	Coef.	*Std. Err.*	*P-value*	*Coef.*	*Std. Err.*	*P-value*
Constant	1.041951	0.438815	0.009	1.04362	0.436855	0.008
Degree of curvature (°/100ft)	6.39E-09	3.36E-09	0.029	6.18E-09	3.33E-09	0.032
Vertical grade (%)	8.38E-09	1.47E-09	0.000	8.81E-09	1.98E-09	0.000
Total right shoulder width	-8.93E-09	3.21E-09	0.003	-9.33E-09	3.20E-09	0.002
Posted speed limit (mi/h)	4.13E-08	2.30E-09	0.000	3.84E-08	2.14E-09	0.000
Posted speed limit squared (mi^2/h^2)	-2.50E-10	2.53E-11	0.000	-2.63E-10	2.13E-11	0.000
AADT per lane (veh/year/lane)	1.08E-11	2.02E-12	0.000	1.01E-11	1.82E-12	0.000
Indicator for interstate highway	-3.50E-07	3.03E-08	0.000	-2.15E-07	2.87E-08	0.000
Indicator for non-interstate freeway	-9.26E-08	3.02E-09	0.000	-9.63E-08	2.00E-08	0.000
Indicator for presence of median	-1.81E-07	3.42E-08	0.000	-1.87E-07	3.34E-08	0.000
Indicator for rolling terrain	2.26E-08	8.77E-09	0.005	2.24E-08	8.76E-09	0.005
Indicator for mountainous terrain	4.05E-08	2.05E-08	0.024	4.04E-08	1.91E-08	0.017
Indicator for rural location	-4.57E-08	1.75E-08	0.005	-4.81E-08	1.74E-08	0.003
Indicator for 2- or 3-lane highway	-7.20E-08	2.21E-08	0.001	-7.18E-08	2.18E-08	0.001
Indicator for 4- or 5-lane highway	1.33E-08	6.31E-09	0.018	1.31E-08	6.13E-09	0.016
Indicator for year 1994	-1.50E-08	6.55E-09	0.011	-1.53E-08	5.79E-09	0.004
Indicator for year 1995	-1.80E-08	7.58E-09	0.009	-1.81E-08	6.05E-09	0.001
Indicator for year 1996	1.61E-08	7.41E-09	0.015	1.58E-08	8.79E-09	0.036
Indicator for year 1999	4.24E-08	8.11E-09	0.000	4.25E-08	8.66E-09	0.000
Indicator for year 2000	5.83E-08	8.31E-09	0.000	5.84E-08	8.52E-09	0.000
Indicator for year 2001	2.93E-09	8.36E-09	0.363			
Indicator for year 2002	-3.10E-09	8.43E-09	0.357			
R-sqrd.			0.9612			0.9618
Nobs.			2,696			2,696

Note: The actual dependent variable in the models presented above is crash count, rather than crash rate. VMT has been interacted with all of the variables shown in the model specification. Consequently, the coefficients presented are crash *rate* coefficient estimates. These coefficients must be multiplied by VMT in order to interpret them as crash *count* effects.

Table 4-21 – Three Example Scenarios for Crash Model Application

Variable description		Scenario I	Scenario II	Scenario III
Degree of curvature (°/100ft)		7.0	4.2	2.1
Vertical grade (%)		4	3	3
Total right shoulder width (ft)		6.5	10.5	12.2
AADT per lane (veh/year/lane)		6,000	2,000	5,000
Indicator for interstate highway		No	no	no
Indicator for non-interstate freeway		No	yes	yes
Indicator for presence of median		No	yes	yes
Indicator for rolling terrain		No	no	no
Indicator for mountainous terrain		No	yes	yes
Indicator for rural location		No	yes	yes
Indicator for 2 or 3 lane highway		Yes	yes	no
Indicator for 4 or 5 highway		No	no	yes
VMT		8,760,000	2,920,000	7,300,000
Speed Limit (mi/h)	Before change	45	50	55
	After change	60	65	70

Note: Data come from observations in the year 1993.

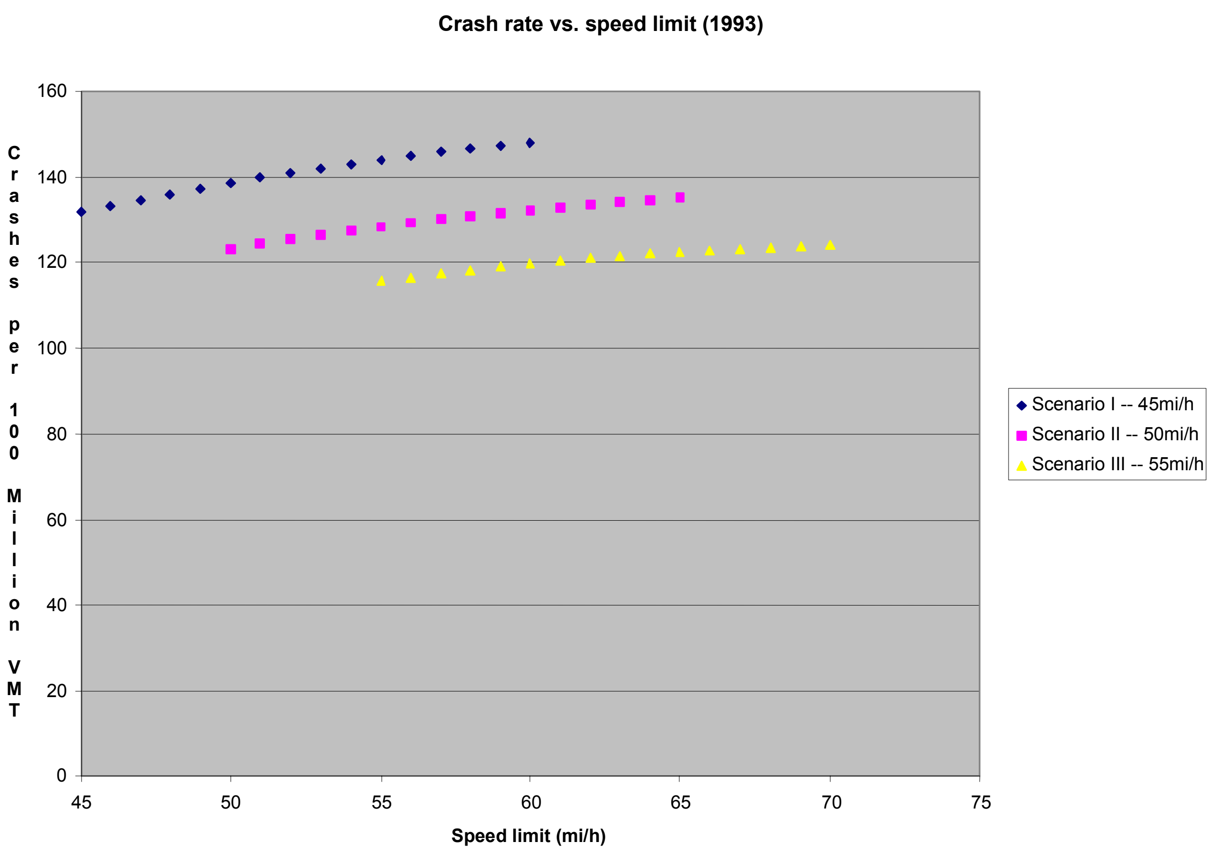

Figure 4-7 – Crash Rates *vs.* Speed Limit in Three Example Scenarios

4.3.2 Model of Crash Count Changes Using HSIS Before-After Data

When a model's dependent variable is influenced not only by the explanatory variables but also by omitted variables that are correlated with them, the estimated effects of the explanatory variables may be biased. (Variables may be omitted because of a specification error, or because data for the variable were not observed or collected and so are not available for use.) In a crash occurrence model, for example, if a segment's crash performance is affected not only by its speed limit but also by unobserved factors (such as sight distance, pavement quality or clear zone width) that are themselves correlated with the speed limit, the estimated effect of the speed limit may be biased because the speed limit coefficient also accounts for the effects of the omitted variables.

A standard way to avoid this problem in datasets that contain repeated observations of one or more individual units (i.e. time series or panel datasets) is by modeling the *differences* between the observations of each unit. To the extent that omitted attributes of the units do not change between observations, this differencing procedure will cause their effects to drop out of an additive model, leaving only the true effects of the included variables.

To this end, a dataset of HSIS segments with constant geometric characteristics was prepared and used in a type of *before-after analysis* of speed limit change effects. This analysis investigated the relationships between *changes* in crash occurrence and changes in speed limits, conditional on roadway geometry.

4.3.2.1 Data Preparation

Out of 100,457 Washington State HSIS segment observations between 1993 and 2002, 41,348 met the requirement of constant geometry, and had a speed limit above 50 mi/h on tangent segments. A clustering procedure similar to the one described in section 4.3.1 produced a dataset of 714 clusters over eight years. (Note that the number of clusters is larger here because the procedure used in the preceding section required the speed limits of segments in a cluster to remain unchanged over the data period, whereas here the speed limit changes are precisely the factors of interest.) The variables and values used for clustering are shown in Table 4-22. The resulting summary statistics of all aggregate cluster variables are shown in Table 4-23.

Table 4-22 – Group Definitions for Clustering Analysis in Crash Count Change Model

	Group description	#groups
# lanes	2 & 3; 4 & 5; 6,7 & 8 lanes	3
Presence of median	yes/no	2
Rural location	yes/no	2
Interstate highway	yes/no	2
Terrain type	Level; rolling; mountainous	3
Non-interstate freeway	yes/no	2
Degree of curvature	DC=0°; 0°<DC≤10°; DC>10°	3
Right shoulder width	RSW=0; 0<RSW≤20; RSW>20 ft	3
Vertical grade	VG=0; 0<VG≤5; VG>5 %	3
Speed limit: before → after	25→25; 30→30; 35→35; 35→40; 40→40; 40→45; 40→50; 40→55; 45→45; 45→50; 50→50; 50→55; 50→60; 55→55; 55→60; 55→65; 55→70; 65→65; 65→70 mi/h	19
Total possible clusters	3×2×2×2×3×2×3×3×3×19=73,872	

Table 4-23 – Summary Statistics of Variables for 714 Segment Clusters

Variables	Mean	Std Dev	Min	Max
Change in crash count per year (after *vs.* before periods)	2.357	8.785	-9.468	121.7
Total crashes per year before SL change	11.09	43.98	0	714.2
Total crashes per year after SL change	13.38	51.22	0	835.9
Segment length (miles)	4.741	26.12	0.05	521.2
VMT before SL change	41612543	189219976	6765	3574365968
VMT after SL change	66215980	299987109	13212	5750583800
Degree of curvature (°/100ft)	1.611	3.306	0	20.32
Vertical grade (%)	2.290	2.254	0	10.00
Indicator for full or partial access control	0.543	0.498	0	1.00
Indicator for interstate highway	0.195	0.396	0	1.00
Indicator for non-interstate freeway	0.349	0.477	0	1.00
Indicator for presence of median	0.534	0.499	0	1.00
Indicator for rolling terrain	0.522	0.500	0	1.00
Indicator for mountainous terrain	0.157	0.364	0	1.00
Indicator for rural	0.555	0.497	0	1.00
Total right shoulder width (ft)	9.023	8.750	0	50.00
Indicator for 2- or 3-lane highway	0.494	0.500	0	1.00
Indicator for 4- or 5-lane highway	0.385	0.487	0	1.00
AADT per lane before SL change	4315	3263	162	17693
AADT per lane after SL change	4610	3541	203	17887
AADT per lane for the whole period	4490	3404	186	17753
SL before change (mi/h)	53.24	7.539	25	65.00
SL after change (mi/h)	55.71	9.065	25	70.00
Number of observations	714 clusters			

4.3.2.2 Model Specification

As before, in order to avoid spurious correlations created by the presence of the *VMT* variable on both sides of the equation, this variable was moved to the model's right-hand side, interacting it with all variables used in the former specification. This again leaves crash count (rather than rate) as the dependent variable. Identical specifications were used for the situations before (*b*) and after (*a*) the speed limit change:

$$Count_a^i = VMT_a^i \times \left(\beta' X_a^i\right) + \varepsilon_a^i \tag{7a}$$

$$Count_b^i = VMT_b^i \times \left(\beta' X_b^i\right) + \varepsilon_b^i \tag{7b}$$

where i designates a segment, $Count_i$ is the crash count on segment i before (*b*) and after (*a*) the speed limit change, and the X^is are segment i's design, use and speed limit variables. The β terms are estimates of the direct impacts that roadway design, use and other explanatory factors have on crash *rates*. When these terms are multiplied by VMT, the resulting product then estimates the effect of the corresponding variable on crash *counts*.

As explained above, *changes in crash counts* were modeled here in order to avoid potential biases caused by correlations between speed limits and omitted variables. The assumption is that the segments' omitted variables would enter the specification additively if they were included, and that their values did not change during the data period. Given the specification of Equations 7, crash count changes for each cluster of roadway segments can be modeled as follows:

$$Count^{i}_{a-b} = Count^{i}_{a} - Count^{i}_{b} = \beta' \times \left(VMT^{i}_{a} X^{i}_{a} - VMT^{i}_{b} X^{i}_{b}\right) + \eta^{i} \qquad (8)$$

where $\eta^{i} = \varepsilon^{i}_{a} - \varepsilon^{i}_{b}$.

For segments experiencing no speed limit changes, the before period covers from January 1, 1993 through March 31, 1996, while the after period covers from April 1, 1996 through December 31, 2002 (skipping years 1997 and 1998, for which Washington HSIS data were not available). For segments experiencing speed limit changes at other times in 1996, the actual date was used to separate the crashes and VMT into before and after periods. Segments experiencing speed limit changes during other years of the panel data period were not used in this analysis, since clustering would require aggregation of data that was felt to be too distinct.

Ordinary least squares regression of crash count changes on the variables listed in Table 4-23 produced, among other results, the OLS residuals associated with each cluster observation. Since crash counts, and thus changes in crash counts, can be expected to rise with VMT, the possible presence of heterscedasticity was of concern, and was examined. Heteroscedasticity does not affect the consistency of OLS estimators, so the individual residuals could be used as consistent estimates of the corresponding error terms. White's test was applied to these to test for error term heteroscedasticity. The null and alternative hypotheses of White's test were:

H_0: $\sigma_i^2 = \sigma^2$ for all *i* (where σ_i^2 is the error term variance for observation *i*);
H_1: $\sigma_i^2 \neq \sigma^2$ for all *i*.

Regression of the squared OLS residuals on the same set of explanatory variables *X* resulted in an R^2 of 0.1086. This value resulted in a White's test chi-squared test statistic[33] of 73.88 *vs.* a 95% critical value of 22.36. Thus the test rejects, as expected, the null hypothesis that the error terms are homoscedastic.

4.3.2.3 Model Estimation and Analysis

The second regression for squared error terms produced estimates of the squared disturbances, which are estimates of the error term variances in the first regression. These estimates were then used as weights in a feasible generalized least squares (FGLS) regression, across segment clusters, of changes in counts of different crash types and in numbers of injured persons and fatalities (equation 8). Regression results for the model of total crash counts are shown in Table 4-24. The R-squared goodness of fit statistic suggests that 96.2% of the variation in total crashes (after dividing by VMT) was explained.

[33] Under the null hypothesis, nR^2 is asymptotically distributed as chi-squared with *K* degrees of freedom, where *n* is the number of observations (714) and *K* is the number of regressors in the second regression (14).

Note that the coefficient estimates shown in Table 4-24 apply not just to the crash count changes modeled by Equation 8, but also to the original crash count specification in Equation 7. As presented, the coefficients in Table 4-24 apply to crash rates (per vehicle mile traveled). They must be multiplied by the *VMT* level (or the change in *VMT* levels) in order to apply to crash counts (or to changes in crash counts).

Table 4-24 – FGLS Model of Changes in Total Crash Counts per VMT

Variables	Coef	Std Error	P-value
Constant	0.852	0.201	0.000
Degree of curvature	6.71E-09	1.16E-09	0.000
Vertical grade	8.34E-09	4.67E-09	0.037
Total right shoulder width	-1.09E-08	2.46E-09	0.000
Speed limit	3.81E-08	1.83E-09	0.000
Speed limit squared	-2.62E-10	4.45E-11	0.000
AADT per lane	1.09E-11	5.77E-12	0.030
Indicator for presence of median	-2.22E-07	2.49E-08	0.000
Indicator for interstate highway	-9.88E-08	2.15E-08	0.000
Indicator for non-interstate freeway	-1.86E-07	3.64E-08	0.000
Indicator for rolling terrain	4.91E-08	1.16E-08	0.000
Indicator for mountainous terrain	1.31E-08	3.73E-09	0.000
Indicator for rural	-4.11E-08	1.19E-08	0.000
Indicator for 2- or 3-lane highway	-7.05E-08	4.24E-09	0.000
Indicator for 4-, or 5-lane highway	1.07E-08	5.02E-09	0.017
Adj. R-sqrd.			0.962
Number of observations			714 clusters

Note: The coefficients in this table should be multiplied by VMT in order to refer to crash *count* effects. As presented, they serve as crash *rate* coefficient estimates.

According to these results, crash rates rise in a concave fashion with speed limits, in a fashion and with coefficients very similar to those obtained in section 4.3.1's models. Of course, since the requirement of unchanging design attributes eliminated many sites from consideration, this analysis is based on far fewer data points than the analysis described in section 4.3.1 (which essentially found a slight increase in crash counts and rates with speed limit, up to a point).

This model can also be used to directly estimate the crash rate increase associated with a 10 mi/h speed limit increase. Given an average road segment in the dataset, the total crash rate is estimated to rise by 2.90% following a speed limit increase from 55 to 65 mi/h. This estimate is very close to the 3.29% increase found, using a different model specification, in section 4.3.1.3. Again, roughly speaking the result is that a 3% increase in total crash rates is associated with a 10 mi/h increase in speed limit.

From these before-after results, several design attributes appear to have a statistically significant effect on changes in crash rates. For example, segments with horizontal curves tend to experience more crashes than tangent segments, everything else constant. Presence of a grade tends to increase crash rates, while the presence of a median helps to reduce crash rates. As before, roadways with 4 or 5 lanes experience the highest crash rates, while roadways with 2 or 3 lanes are estimated to have the lowest crash rates. More traffic (or AADT per lane) is associated with a higher crash rate.

Based on calculations involving the parameter estimates and average control variable values of Table 4-24, speed limits, right shoulder width, degree of curvature and presence of a median are the most important factors affecting crash frequency. For example, a 10 ft increase in shoulder width is expected to result in a total crash rate reduction of 4.49%. And the addition of a median, other things equal, is expected to reduce crash rates by a sizable 9.0%. These values are similar to those for the models of crash counts (Table 4-20). A summary of results from both sets of crash count models is presented following the discussion of crash severity models (using the HSIS segment-based datasets), in Tables 4-26 and 4-27. In general, the estimates are highly similar across models. Tables 4-26 and 4-27 allow one to appreciate the effects of variables on crash severity as well as crash frequency.

In addition to the models of total crash counts discussed previously, the project also estimated models of crash count by crash and injury severity. These latter models proved to be unsatisfactory, most likely because the dependent variables do not satisfy the distribution assumptions of least squares regression. Similarly, the project also specified and estimated models in which speed limits were interacted with other explanatory variables. Most of the interaction terms in these models were not statistically significant, and the squared speed limit term was dropped due to collinearity.

Comparing the model of crash count changes discussed in this section with the model of crash counts discussed in the preceding section, it can be seen that the estimated coefficients are consistent in terms of sign, but vary somewhat in magnitude. Some variables, such as shoulder width and squared speed limit, are statistically significant in the basic crash count model but not in the crash count change model. However, the crash count change model addresses the issue of potential correlations between speed limits and omitted variables. For this reason, the results of the present model of crash count changes are preferred to those of the basic crash count model.

4.4 Injury Severity Models

Injury severity models are concerned with predicting the distribution of injuries by severity, given that a crash has already occurred and persons are involved. To investigate the factors affecting injury severity, the project applied standard (homoscedastic) ordered logit as well as heteroscedastic ordered logit regression models for analysis of two key datasets:

- The Washington occupant-based database (section 4.4.1), and
- The National Automotive Sampling System's Crashworthiness Data System (NASS CDS) (section 4.4.2).

The first of these two datasets is particularly rich in roadway design attributes. Moreover, it ties clearly to the crash frequency models (as developed in section 4.3). The latter offers a much more comprehensive sample of crashes, by relying on a national data base. It also controls for vehicle weight (and type), which is a valuable addition to such models. Both models offer very similar results with respect to the impacts of speed limits. However, both are cross-sectional in nature and may not provide the most appropriate picture of actual driver responses to (and thus crash injury outcomes following) *changes* in speed limits.

The ordered logit (OL) specification is an appropriate approach when the outcome being modeled can be naturally represented by an ordered sequence of discrete values. For example, the occupant of a crash may experience no injury, minor injury, severe injury or death. Heteroscedasticity recognizes variance in the latent error term, allowing for more behavioral flexibility. The datasets and the model results are discussed below.

4.4.1 Heteroscedastic Ordered Logit Model of Crash Severity Using HSIS Data

4.4.1.1 Data Preparation

This analysis used the disaggregate Washington State occupant-based crash datasets from 1993 to 1996. Descriptions and summary statistics of all variables can be found in Table 4-25.

Table 4-25 – Summary Statistics for the HSIS Crash Severity Dataset

Description of Variables of Interest	Min	Max	Mean	Std. Dev
Injury severity: 1=no injury; 2=possible injury; 3=non-disabling injury; 4=disabling injury; 5=fatal	1	5	1.462	.8044
Roadway Design Features				
Horizontal curve length (ft)	0	12683	391.9	784.5
Degree of curvature (°/100ft)	0	23.97	.8028	1.722
Vertical curve length (ft)	0	6700	523.4	547.1
Vertical grade (%)	0	11.11	1.724	1.577
Total right shoulder width (ft)	0	52	11.52	8.011
Number of lanes	2	9	4.310	2.132
Presence of median (1=median, 0=no median)	0	1	.5628	.4960
Speed limit (mi/h)	25	65	54.67	6.053
Road Use, Location & Terrain				
Annual Average Daily Traffic (AADT) per lane	47.5	48251	11970	9366
Indicator for rural: 1=rural; 0=otherwise	0	1	.3700	.4828
Indicator for rolling terrain: 1=rolling terrain; 0=otherwise	0	1	.1932	.3948
Indicator for mountainous terrain: 1=mountainous terrain; 0=otherwise	0	1	.0290	.1679
Road Class & Access Control				
Indicator for interstate: 1=interstate; 0=otherwise	0	1	.4104	.4919
Indicator for limited access: 1=limited access; 0=otherwise	0	1	.6313	.4825
Road Surface Condition & Light Condition				
Indicator for dry road surface condition: 1=dry; 0=otherwise	0	1	.6380	.4806
Indicator for snow road surface condition: 1=snow; 0=otherwise	0	1	.0395	.1948
Indicator for ice road surface condition: 1=ice; 0=otherwise	0	1	.0700	.2551
Indicator for wet road surface condition: 1=wet; 0=otherwise	0	1	.2525	.4344
Indicator for daylight: 1=daylight; 0=otherwise	0	1	.6919	.4617

Seat Position				
Indicator for driver: 1=driver; 0=other passengers	0	1	.6955	.4602
Indicator for front passenger: 1=front passengers; 0=otherwise	0	1	.1926	.3943
Indicator for rear passenger: 1=rear passengers; 0=otherwise	0	1	.0957	.2942
Restraint Use & Residential Distance to Where Crashes Occurred				
Indicator restraint use: 1=no restraints used; 0=otherwise	0	1	.0686	.2528
Indicator for residents within 15 miles; 1=residents within 15 miles; 0=otherwise	0	1	.7023	.4573
Driver Gender, Alcohol Consumption & Others				
Indicator for female: 1=female; 0=otherwise	0	1	.4099	.4918
Indicator for if the driver had been drinking (HBD) prior to a crash: 1=HBD; 0=otherwise	0	1	.0642	.2451
Number of vehicles involved	1	10	2.075	.8301
Indicator for year 1993: 1=year 1993; 0=otherwise	0	1	.2342	.4235
Indicator for year 1994: 1=year 1994; 0=otherwise	0	1	.2531	.4348
Indicator for year 1995: 1=year 1995; 0=otherwise	0	1	.2440	.4295
Indicator for year 1996: 1=year 1996; 0=otherwise	0	1	.2687	.4433
Number of Observations				197376

4.4.1.2 Model Specification

The ordered logistic model is formally specified as follows (Greene, 2000):

$$Y_i^* = X_i'\beta + \varepsilon_i \tag{1}$$

where $i = 1,2,\ldots n$ designates an observation (occupant), Y_i^* is a latent continuous measure of injury severity for occupant i, X_i is a vector of occupant i characteristics relevant in explaining the injury severity, β is a vector of parameters to be estimated, and ε_i is an unobservable error term, assumed to be identically and independently distributed as a logistic random variable.

The observed, discrete severity level variable Y_i can be computed using the following equation:

$$Y_i = \begin{cases} 1 & \text{if} \quad Y_i^* \le \mu_1 = 0 & \text{no injury} \\ 2 & \text{if} \quad \mu_1 < Y_i^* \le \mu_2 & \text{possible injury} \\ 3 & \text{if} \quad \mu_2 < Y_i^* \le \mu_3 & \text{non-disabling injury} \\ 4 & \text{if} \quad \mu_3 < Y_i^* \le \mu_4 & \text{disabling injury} \\ 5 & \text{if} \quad Y_i^* > \mu_4 & \text{fatal} \end{cases} \tag{2}$$

where μ_1 is a threshold value fixed at 0, and μ_2, μ_3 and μ_4 are threshold parameters to be estimated.

The probabilities corresponding to each discrete crash severity can be obtained via the following equation:

$$
\begin{aligned}
P(Y_i = j) &= P(\mu_{j-1} < Y_i^* \le \mu_j) \\
&= P\left(\varepsilon_i \le \mu_j - X_i'\beta\right) - P\left(\varepsilon_i \le \mu_{j-1} - X_i'\beta\right) \\
&= F\left(\mu_j - X_i'\beta\right) - F\left(\mu_{j-1} - X_i'\beta\right)
\end{aligned} \tag{3}
$$

where $F(\cdot)$ represents the standard logistic distribution function, and $j = 1, 2, \ldots, 5$. For injury severity levels (Y_i) of 1 or 5, extreme thresholds μ_0 and μ_5 apply in this equation. These are negative and positive infinity, respectively, representing the two tails of the logistic distribution.

The log-likelihood function can be constructed as follows.

$$LogL = \sum_{i=1}^{n} \sum_{j=1}^{5} \left\{ \ln\left[F\left(\mu_j - X_i'\beta\right) - F\left(\mu_{j-1} - X_i'\beta\right) \right] \right\} \tag{4}$$

The log-likelihood in Equation (4) is maximized with respect to all parameters (β, μ_2, μ_3 and μ_4) to obtain maximum likelihood estimates (MLE) of the parameters.

If error terms are heteroscedastic, the assumption of constant error term variance fails. The error term distribution then becomes $\varepsilon_i \sim F\left(0, \sigma_i^2\right)$, and the log-likelihood function becomes:

$$LogL = \sum_{i=1}^{n} \sum_{j=1}^{5} \left\{ \ln\left[F\left(\frac{\mu_j - X_i'\beta}{\sigma_i}\right) - F\left(\frac{\mu_{j-1} - X_i'\beta}{\sigma_i}\right) \right] \right\} \tag{5}$$

Here σ_i^2 is parameterized in terms of a set of variables Z_i and an associated parameter set γ. A log-linear specification is commonly used to ensure positive σ_i^2. Thus, the following was used:

$$F(x) = \left(1 + \exp(-x)\right)^{-1} \tag{6}$$

$$\sigma_i^2 = \left(\exp\left(Z_i\gamma\right)\right)^2 \tag{7}$$

Note that a standard OL model, which assumes homoscedasticity, restricts γ to 0 and σ_i^2 to 1 for all occupants.[34] In contrast, HOL models allow the unobserved factors to vary, providing greater flexibility and realism. As an example of the modeling advantages provided by this flexibility, consider modeling the injury severity properties of speed limits. Roadways with higher speed limits usually are built to higher design standards, which may help protect occupants in a crash; but higher speeds add energy to crashes, resulting in more severe injuries, everything else constant. The combination of these two effects may result in greater uncertainty regarding crash outcomes. In this way speed limits may contribute to higher variance of the unobserved error terms in the ordered logit models, a feature permitted by the HOL specification.

[34] If the variance of the random error component were not specified, a second threshold value would require specification. If the model's constant term were set to zero, no threshold terms would be specified. Such specifications permit statistical identification of model parameters.

4.4.1.3 Model Estimation and Analysis

An HOL regression model was estimated using the Washington State occupant data for years 1993 through 1996[35], and results are shown in Table 4-26. The table includes an initial model as well as a final model, in which explanatory variables not exhibiting statistical significance at the 0.1 level have been removed via a process of step-wise deletion (Greene, 2002).

Variables of every type were informative in the final model. Injuries on sharper horizontal curves were found to be more severe, while injuries on steeper vertical curves were found to be less severe.[36] Other things equal, crashes on access controlled highways tend to be less severe.

Linear and squared speed limit terms serve as key explanatory variables in the heteroscedastic models. Both linear and squared speed limit terms are highly statistically significant in the base model of latent injury severity (Y^*), and a linear speed limit term is statistically significant in the model of variance. The positive signs suggest that higher speed limits tend to be associated with higher variations in the latent injury severity measure. However, there is a concave effect, due to the negative coefficient on the square speed limit term. Taking all this into account, the probability of disabling injury and death are estimated to be highest when the speed limit is 79 mi/h. A similar result is found when using the NASS occupant data, as discussed below in section 4.4.2. Note, however, that these values should not be taken literally, since they involve extrapolation beyond the range of the estimation dataset.

These results were used to predict percentage changes in the probability of experiencing different injury severities following a speed limit change, given that a crash occurs. Results are shown in Table 4-27 for a number of before/after speed limits, including some (e.g. 50 mi/h to 70 or 75 mi/h) that would not often occur in practice. For more typical speed limit increases, increases in the fatality probability in the range of 20 to 30% are predicted. This does not mean that the total number of predicted fatalities will increase by 20 to 30%; rather, it means that that *if* a crash occurs, the probability of a resulting fatality increases by that amount.

To compare these results with the crash occurrence models presented previously, consider a segment of highway having the same "average" characteristics as discussed in section 4.3.1. For a speed limit increase from 55 mi/h to 65 mi/h, the basic crash count model presented in section 4.3.1 predicts a 3.29% increase in the crash rate. According to Table 4-27, if the speed limit increases from 55 to 65 mi/h, the probability of fatal injury would rise 24%; the corresponding probability changes for other injury severity levels would be 8.46% (disabling injury), 4.77% (non-disabling injury), -0.14% (possible injury) and 5.23% (no injury).

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[35] An HOProbit model was run as well, and the estimator associated with speed limit was also positive in the model of error-term variance, but it was not statistically significant. Because the speed limit variable did not appear in the final model's variance specification, the maximum crash severity was estimated to occur at 63 mph. In order to remain consistent with the NASS work that follows here, the HOL specification was chosen.

[36] The dataset includes segments with various grades, but does not indicate if a crash occurred on the uphill or downhill direction. It may be that vehicles going uphill are slowed enough that the reduction in severity more than compensates for the downhill severity increases that one might expect a priori. Actual speed data was not available.

Table 4-26 – Heteroscedastic Ordered Logit Regression Model of Occupant Injury Severity – Washington HSIS Data

	Initial Model				Final Model			
	Coeff.	**Std.Err.**	**t-ratio**	**P-value**	**Coeff.**	**Std.Err.**	**t-ratio**	**P-value**
Latent Injury Severity Measure								
Intercept	-4.583E+00	6.292E-01	-7.283	0.000	-3.765E+00	2.455E-01	-15.34	0.000
Roadway Design Features								
CURV_LENGTH	-1.798E-05	1.168E-05	-1.539	0.124	-1.733E-05	8.462E-06	-2.048	0.041
DEG_CURVE	7.465E-03	6.347E-03	1.176	0.240	1.059E-02	3.821E-03	2.771	0.006
VCUR_LENGTH	-3.920E-05	1.758E-05	-2.230	0.026	-2.855E-05	1.195E-05	-2.389	0.017
PCT_GRADE	-6.597E-03	5.414E-03	-1.218	0.223	-7.276E-03	3.140E-03	-2.317	0.021
RSHLDRWIDTH	3.065E-04	1.273E-03	0.241	0.810				
NUMLANES	-4.686E-03	6.960E-03	-0.673	0.501				
MEDIAN	1.110E-01	4.233E-02	2.622	0.009	6.228E-02	2.154E-02	2.891	0.004
SPDLMT	9.714E-02	1.338E-02	7.261	0.000	8.327E-02	8.930E-03	9.325	0.000
SPDLMTSQ	-7.933E-04	1.252E-04	-6.339	0.000	-6.826E-04	8.993E-05	-7.590	0.000
Road Use, Location & Terrain								
AADTPERLANE	9.389E-06	2.387E-06	3.933	0.000	7.033E-06	1.089E-06	6.460	0.000
RURAL	1.222E-01	3.588E-02	3.406	0.001	9.028E-02	2.056E-02	4.392	0.000
MOUNTAINOUS	-2.227E-01	8.410E-02	-2.648	0.008	-1.610E-01	3.992E-02	-4.034	0.000
ROLLING	-2.399E-03	2.321E-02	-0.103	0.918				
Road Class & Access Control								
INTERSTATE	-4.995E-02	3.874E-02	-1.289	0.197	-3.744E-02	1.799E-02	-2.081	0.037
LIMTEDACCESS	-1.451E-01	4.191E-02	-3.461	0.001	-1.046E-01	2.282E-02	-4.583	0.000
Road Surface Condition & Light Condition								
SNOW	-3.686E-01	8.812E-02	-4.183	0.000	-2.812E-01	4.373E-02	-6.432	0.000
ICE	-5.964E-02	3.804E-02	-1.568	0.117	-4.667E-02	2.777E-02	-1.681	0.093
WET	7.373E-02	2.158E-02	3.416	0.001	5.639E-02	1.285E-02	4.389	0.000
DAYLIGHT	-9.105E-02	2.392E-02	-3.807	0.000	-6.978E-02	1.341E-02	-5.205	0.000
Seat Position								
DRIVER	-2.338E-02	1.852E-02	-1.263	0.207				
PASSENGERREAR	-4.087E-01	8.264E-02	-4.946	0.000	-2.990E-01	2.658E-02	-11.25	0.000
Restraint Use & Residential Distance to Crash Site								
RESTUSE	1.733E+00	3.219E-01	5.384	0.000	1.322E+00	6.558E-02	20.16	0.000
RESID15M	2.648E-01	5.294E-02	5.002	0.000	2.015E-01	1.618E-02	12.46	0.000
Driver Gender, Alcohol Consumption & Others								
FEMALE	7.484E-01	1.391E-01	5.379	0.000	5.732E-01	2.910E-02	19.69	0.000
DRINKING	7.727E-01	1.464E-01	5.276	0.000	5.881E-01	3.623E-02	16.23	0.000
YEAR1994	7.292E-02	2.546E-02	2.863	0.004	4.235E-02	1.377E-02	3.075	0.002
YEAR1995	3.506E-02	2.352E-02	1.491	0.136				
YEAR1996	-8.752E-02	3.008E-02	-2.909	0.004	-8.162E-02	1.255E-02	-6.504	0.000

Heteroscedastic Ordered Logit Regression Model of Occupant Injury Severity (Cont'd)

	Initial Model				Final Model			
	Coeff.	**Std.Err.**	**t-ratio**	**P-value**	**Coeff.**	**Std.Err.**	**t-ratio**	**P-value**
Variance of Latent Injury Severity Measure								
CURV_LENGTH	1.566E-05	5.280E-06	2.965	0.003	1.877E-05	4.803E-06	3.908	0.000
DEG_CURVE	4.214E-03	3.107E-03	1.356	0.175				
VCUR_LENGTH	4.167E-05	7.787E-06	5.352	0.000	4.053E-05	7.509E-06	5.398	0.000
PCT_GRADE	-2.738E-03	2.622E-03	-1.044	0.296				
RSHLDRWIDTH	1.617E-03	7.274E-04	2.223	0.026	1.641E-03	5.253E-04	3.124	0.002
NUMLANES	-2.785E-02	3.887E-03	-7.165	0.000	-2.931E-02	2.537E-03	-11.55	0.000
MEDIAN	-1.715E-02	1.766E-02	-0.971	0.332				
SPDLMT	1.563E-02	7.301E-03	2.140	0.032	5.618E-03	9.207E-04	6.102	0.000
SPDLMTSQ	-9.421E-05	7.295E-05	-1.291	0.197				
AADTPERLANE	-1.742E-05	7.868E-07	-22.14	0.000	-1.717E-05	6.750E-07	-25.44	0.000
RURAL	7.714E-02	1.257E-02	6.135	0.000	8.026E-02	1.206E-02	6.654	0.000
MOUNTAINOUS	1.910E-02	2.876E-02	0.664	0.507				
ROLLING	1.259E-02	1.065E-02	1.182	0.237				
INTERSTATE	7.069E-03	1.923E-02	0.368	0.713				
LIMTEDACCESS	3.103E-02	1.416E-02	2.191	0.028	2.351E-02	1.258E-02	1.869	0.062
SNOW	-5.448E-02	2.274E-02	-2.396	0.017	-5.375E-02	2.251E-02	-2.388	0.017
ICE	-2.759E-02	1.621E-02	-1.702	0.089	-2.639E-02	1.612E-02	-1.637	0.102
WET	-7.445E-02	9.099E-03	-8.183	0.000	-7.395E-02	9.070E-03	-8.153	0.000
DAYLIGHT	-1.915E-02	8.552E-03	-2.239	0.025	-1.879E-02	8.545E-03	-2.199	0.028
DRIVER	1.854E-02	9.373E-03	1.978	0.048	1.123E-02	7.630E-03	1.472	0.141
PASSENGERREAR	3.962E-02	1.586E-02	2.497	0.013	3.474E-02	1.542E-02	2.253	0.024
RESTUSE	1.600E-01	1.166E-02	13.73	0.000	1.590E-01	1.163E-02	13.67	0.000
RESID15M	-8.052E-02	9.355E-03	-8.607	0.000	-8.041E-02	9.203E-03	-8.738	0.000
FEMALE	-1.225E-01	8.098E-03	-15.12	0.000	-1.238E-01	8.062E-03	-15.36	0.000
DRINKING	2.060E-01	1.405E-02	14.66	0.000	2.066E-01	1.404E-02	14.71	0.000
YEAR1994	-2.909E-02	1.101E-02	-2.643	0.008	-2.456E-02	9.225E-03	-2.663	0.008
YEAR1995	-3.736E-02	1.141E-02	-3.275	0.001	-2.793E-02	8.043E-03	-3.473	0.001
YEAR1996	-2.963E-03	1.166E-02	-0.254	0.799				
Thresholds								
Mu(1)	1.442E+00	2.672E-01	5.398	0.000	1.099E+00	5.220E-02	21.05	0.000
Mu(2)	3.988E+00	7.390E-01	5.397	0.000	3.038E+00	1.447E-01	21.00	0.000
Mu(3)	7.145E+00	1.325E+00	5.394	0.000	5.442E+00	2.618E-01	20.79	0.000
#Observations	197349				197349			
Log-L at Convergence	-166823				-166829			
Log-L at Constant	-176596				-176596			
LRI	0.05534				0.05531			

Table 4-27 – Effect of Speed Limit on Occupant Injury Severity – Washington HSIS Data

Speed Limit Before Change	Speed Limit After Change	Percentage Change in Probability				
		No Injury	Possible Injury	Non-incapacitating Injury	Incapacitating Injury	Killed
50 mi/h	70 mi/h	0.40%	-10.08%	-2.47%	18.25%	54.94%
55 mi/h	65 mi/h	5.23%	-0.14%	4.77%	8.46%	24.18%
55 mi/h	70 mi/h	2.56%	-7.95%	-4.01%	9.19%	32.95%
60 mi/h	70 mi/h	3.14%	-5.52%	-3.98%	3.58%	17.63%
60 mi/h	75 mi/h	6.63%	-8.45%	-7.55%	2.22%	22.97%
65 mi/h	70 mi/h	2.22%	-2.87%	-2.61%	0.67%	7.06%
65 mi/h	75 mi/h	5.68%	-5.89%	-6.23%	-0.65%	11.92%

Note: Probabilities are calculated while evaluating all other variables at their average values. In this context, an average roadway section refers to a section with 2°/100ft degree of curvature (392ft), 2% vertical grade (523ft), on a four-lane divided rural interstate highway, with 10 ft shoulder width, and carrying 6,000 AADT per lane in the year 1996. The crash occurred on a dry road section during daylight hours. The average occupant is a male driver using a restraint, legally sober and driving within 15 miles of his residence.

Table 4-28 – Effect of Speed Limit on Injury Rates with the Three Scenarios in Section 4.3.1.3 – Washington HSIS Data

Speed Limit Before Change	Speed Limit After Change	Change in injury rates (per 100 million VMT)				
		No Injury	Possible Injury	Non-incap. Injury	Incapacitating Injury	Killed
45 mi/h	60 mi/h	2.65	1.83	7.18	4.56	1.19
50 mi/h	65 mi/h	5.23	0.94	4.39	3.45	1.06
55 mi/h	70 mi/h	3.25	0.09	3.23	2.93	0.94

Note: Crash rates are calculated while evaluating all other variables at their average values. In this context, an average roadway section refers to a section with 2°/100ft degree of curvature (392ft), 2% vertical grade (523ft), on a four-lane divided rural interstate highway, with 10 ft shoulder width, and carrying 6,000 AADT per lane in the year 1996. The crash occurred on a dry road section in daytime. The results are quite stable, however, and these percentages are very similar for other roadway characteristics.[37]

4.4.2 Heteroscedastic Ordered Logit Model of Injury Severity Using NASS CDS Data

In contrast to the data used in the preceding section, data here come from roadways of all speeds across the U.S. The data do not contain as many design variables as the Washington State HSIS, but do include vehicle weight and type. Vehicle type is a proxy for a variety of structural factors that can affect crash dynamics and their repercussions on vehicle occupants. Moreover, the kinetic energy released in a crash is directly proportional to a vehicle's weight. Vehicle weight information, however, is not recorded in most crash datasets, so this application is rather unusual. Model specifications are the same as those in section 4.4.1, and the speed-limit results are very similar. However, observational weights are used here, to reflect underreporting of crashes and a more nationally representative distribution of the NASS sample data. Moreover, two- and one-vehicle crashes are analyzed separately. These data and their model results are discussed below.

[37] Note: Tables 4-27 and 4-28 only present the percentage changes in probability (or crash rate) based on the estimated models. The numbers in the two tables are for illustration only. Moreover, in the datasets there is no speed limit above 70 mi/h, so the 75 mi/h cases are an extrapolation.

4.4.2.1 Data Preparation

The estimation dataset was developed using the National Automotive Sampling System's Crashworthiness Data System (NASS CDS) for the years 1998 through 2001. The NASS CDS collects crash data in 24 areas (also called primary sample units, or PSUs) in 17 states in the U.S. All crashes included in the NASS CDS are police reported, involved property damage and/or personal injury, and resulted in at least one towed passenger car or light truck or van. Data are sampled in a stratified fashion, first among PSUs, then among police jurisdictions, and lastly among reported crashes (NHTSA 2000b). The crashes in the dataset represent just 0.05 percent of all police-reported crashes in the U.S, which is less than most other nationally collected crash datasets. However, the dataset is reasonably representative, in the sense that it considers all but the most minor crash severities, on all roads, and in a representative sample of geographic units. Note that the analysis described here considered all crashes in the dataset, and did not filter out those occurring on roads with speed limits below 55 mi/h.

Each observation in the sample data is given a population expansion factor called a Ratio Inflation Factor (RIF), which is the inverse of the probability of selecting that crash from crashes nationwide. These weights are estimated by NASS researchers based on a three-stage sampling method.

It is important to note that CDS data, like those in most crash datasets, are not totally unbiased with respect to crash severity. More severe crashes are more likely to be reported and thus recorded. The RIFs are supposed to reflect a crash's probability of selection and so to account for selection biases, but some uncertainty remains. Moreover, different PSUs have different criteria for reporting their crash data (such as a minimum crash cost or severity). This causes some geographic heterogeneity in the data. Nonetheless, among all available datasets, the NASS CDS is very appropriate for this study because of its comparatively unbiased (i.e., national in nature) sample. Moreover, it offers detailed information on vehicle weight, which is a valuable variable to consider.

Information on vehicles and occupants was merged in order to produce an occupant-based dataset. There were 18,609 complete occupant observations for two-vehicle crashes and 7,628 for one-vehicle crashes. These represented 53.6 percent and 77.8 percent of the NASS CDS sample data for such crash occupants, respectively. The dependent variable, injury severity, was missing in 6,036 occupant observations, accounting for many of the invalid observations. Other variables missing in significant numbers included occupant age and gender, seat belt usage, vehicle curb weight, occupant seat type, and weight of the collision partner. Less severe injuries and passenger cars as collision partners were slightly under-represented in the data analyzed here. Bucket seat types were over-represented in both models. Furthermore, because the NASS CDS does not provide curb weights for medium and heavy-duty trucks, these were assumed to weigh 25,000 lbs. Any overall bias in this assumption will be reflected in the indicator variable used for medium and heavy trucks in the model specification.

Table 4-29 provides the definitions and summary statistics of variables in the estimation dataset.

4.4.2.2 Model Specification

The injury severity model developed here is based on a heteroscedastic ordered logit (HOL) model specification (Alvarez and Brehm, 2002), as described in section 4.4.1.2. However, since the NASS data differ from the Washington case, there are a few distinctions. One is the use of observation-level weight factors, which results in the following likelihood function:

$$L = \prod_{j=1}^{J} \prod_{i=1}^{n} \left(F\left(\frac{\mu_j - x_i \beta}{\sigma_i} \right) - F\left(\frac{\mu_{j-1} - x_i \beta}{\sigma_i} \right) \right)^{w_{ij}} \tag{5}$$

Here w_{ij} is the weight or expansion factor for the i^{th} observation (i.e., occupant) experiencing injury severity level j. (Sample unit expansion factors are provided in the NASS CDS dataset, and these recognize that certain crashes are relatively underreported.[38])

For the model used in this analysis of the NASS data, the variance is parameterized as a function of speed limit, vehicle type and vehicle curb weight (rather than all potential variables, as done in the analysis in section 4.4.1 of the Washington data [which lack vehicle weight information]). Incorporation of speed limit as an explanatory variable in the variance specification is based on O'Donnell and Connor's (1996) similar use of travel speed (or an officer's estimate of the vehicle's speed, before the collision, and thus a variable that is missing in most crash observations used here). Vehicle type and weight are included because they represent many unobserved vehicle features (such as stiffness and structure) and can offer new insights (since they are rarely controlled for).

Another distinction is that the NASS CDS occupant-level observations were characterized by number of involved vehicles; and severity models for single-vehicle and multi-vehicle crashes were run separately, to observe whether that distinction had any effect on predicted outcomes. Indeed it did, as discussed below.

4.4.2.3 Model Estimation and Analysis

Table 4-30 provides HOL and OL estimation results for one-vehicle and two-vehicle collisions separately. Linear and squared speed limit terms serve as key explanatory variables in these models. It can be seen that both the linear and squared speed limit terms are highly statistically significant for y^* (the latent injury severity measure), but that individually they do not have statistically significant effects on its variance. This does not necessarily mean that speed limits have no overall effect on crash severity variance, but only that the speed limit-related variables in the particular specification considered here are not individually significant. In fact, they have practically significant effects that are evident in the estimates of crash severity.

In the case of one-vehicle crashes, the probability of injury and death are estimated to be highest when the speed limit is 60 mi/h. However, in two-vehicle crashes, roads with higher speed limits have a higher proportion of fatal crashes. Taking into account the relative proportion of one- and

[38] Strictly speaking, the observation weights are crash-based. Applying these weights to observations of occupant injury severity is not completely correct, but is nonetheless considered a reasonable approximation.

two-vehicle crashes, the overall effect of increasing speed limits is to deteriorate safety performance by increasing the probability of more severe crashes. Zhang *et al*. (2000), Krull *et al*. (2000) and Khattak *et al*. (2002) all found that higher speed limits are associated with more severe injuries. The present work shows results consistent with theirs.

The overall effect of speed limit changes on injury severity estimates is shown in Table 4-31. Focusing on typical speed limit increases, the percentage changes in proportion of fatal injuries are estimated to range from 31% (for a 65 to 70 mi/h speed limit increase, in the case of an "average" NASS observation) to 110% (for a 55 to 70 mi/h speed limit increase). These same estimates range from 12% to 55% for the results obtained with the HOL model of Washington HSIS data, as shown in Table 4-27. The model estimated using NASS data predicts uniformly much higher incapacitating injury and fatality impacts than the one estimated from HSIS data. This may be due to the NASS database including roadways of all levels of speed limit, rather than focusing only on high-speed roadways. By covering a greater range of roadway types, the model may be less accurate in predictions at extreme speed limit levels, such as high speed cases.

Considering that the crash rate itself increases with a speed limit increase (a 2.9% to 3.3% increase is associated with a 10 mi/h speed limit increase; see section 4.3), overall fatality rates are predicted to rise by slightly higher percentages than those shown in Tables Table 4-27 and Table 4-31. The association between speed limit and injury severity dominates the overall result.

However, as alluded to earlier, both databases for the severity analyses are cross-sectional in nature and therefore cannot really replicate the severity consequences of speed limit *changes*. As discussed in section 4.2.3, driver responses to speed limit changes are relatively moderate (e.g., 3 mi/h for a 10 mi/h speed limit change) when compared to a cross-sectional examination of speeds on roadways whose limits have not changed (e.g., 6 mi/h for a 10 mi/h limit increase). If actual speed choice responses are half those one would expect from an examination of cross-sectional data, it is very possible that the actual percentage changes in severe crash outcomes would be less than half those predicted (in Table 4-27 and Table 4-31) due to the convex nature of the (estimated) severity relationship and speed limits.

Table 4-29 – Summary Statistics of HOL Injury Severity Model Data – NASS CDS Data

Variable	Variable Description	One-vehicle Crashes		Two-vehicle Crashes	
		Weighted Mean	Weighted Std. Dev.	Weighted Mean	Weighted Std. Dev.
Vehicle Weight and Type					
#CURBWGT	Curb weight of the vehicle, in 100 lbs	31.675	7.204	30.395	7.226
#CURBWGTSQD	Square of vehicle curb weight, in 10000 lbs^2	1055	536	976	522
#VEHAGE	Vehicle age, in years	7.298	6.545	6.656	5.011
CAR	1 if the vehicle is a CAR; 0 otherwise	Base variable for vehicle type			
#MINIVAN	1 if the vehicle is a minivan; 0 otherwise	0.039	0.193	0.087	0.282
#SUV	1 if the vehicle is an SUV; 0 otherwise	0.214	0.410	0.081	0.273
#PICKUP	1 if the vehicle is a pickup; 0 otherwise	0.127	0.333	0.093	0.291
*PNVEHWGT	Curb weight of the collision partner, in 100 lbs	---	---	49.155	58.019
*PNVEHWGTSQD	Square of the collision partner curb weight, in 10000 lbs^2	---	---	5782	16258
PNCAR	1 if the collision partner is a car; 0 otherwise	Base variable for partner vehicle type			
*PNMINIVAN	1 if the collision partner is a minivan; 0 otherwise	---	---	0.113	0.316
*PNSUV	1 if the collision partner is an SUV; 0 otherwise	---	---	0.081	0.273
*PNPICKUP	1 if the collision partner is a pickup; 0 otherwise	---	---	0.165	0.372
*PNMDTHDT	1 if the collision partner is a medium or heavy-duty truck; 0 otherwise	---	---	0.076	0.265
Seating and Seat Belts					
BUCKET	1 if the seat is a integral bucket; 0 otherwise	Base variable for seat type			
FOLDINGBUCKET	1 if the seat is a bucket with folding back; 0 otherwise	0.263	0.440	0.253	0.435
BENCHSEAT	1 if the seat of the occupant is a integral bench; 0 otherwise	0.072	0.258	0.077	0.267
SEPBENCH	1 if the seat is a bench with separate cushion; 0 otherwise	0.098	0.297	0.104	0.305
FOLDINGBENCH	1 if the seat is a bench with folding cushion; 0 otherwise	0.165	0.371	0.126	0.332
OTHERSEAT	1 if the seat is pedestal or box mounted; 0 otherwise	0.029	0.169	0.044	0.205
NOBELT	1 if the occupant does not use any belt; 0 otherwise	Base variable for seat belt usage			
LAPSHOU	1 if the occupant uses lap and shoulder belt; 0 otherwise	0.550	0.497	0.545	0.498
OTHEBELT	1 if the occupant uses shoulder only or lap only belt; 0 otherwise	0.204	0.403	0.316	0.465

Summary Statistics of the HOL Injury Severity Model Estimation Dataset (Cont'd)

Variable	Variable Description	One-vehicle Crashes		Two-vehicle Crashes	
		Weighted Mean	Weighted Std. Dev.	Weighted Mean	Weighted Std. Dev.
Roadway Design and Environmental Factors					
GOODWEATHER	1 if the weather is good; 0 otherwise	Base variable for weather			
BADWEATHER	1 if the weather is adverse, including snowy, rainy, foggy and smoky; 0 otherwise	0.215	0.411	0.190	0.392
LIGHT	1 if the light condition is daylight; 0 otherwise	Base variable for light condition			
DARK	1 if the light condition is dark or dawn; 0 otherwise	0.543	0.498	0.265	0.441
#SPDLIMIT	Speed limit of the site, in mi/h	44.568	14.415	40.546	10.236
#SPDLIMITSQD	Square of the site speed limit, in mi/h^2	2194.052	1364.361	1748.772	887.773
NODIVISION	1 if the roadway is two-way yet not divided; 0 otherwise	Base variable for road division			
NONPOSITIVEDIV	1 if the roadway is divided by vegetation, water, trees, embankments, ravine ; 0 otherwise	0.144	0.351	0.222	0.415
POSITIVEDIV	1 if the roadway is divided by manufactured barriers; 0 otherwise	0.125	0.331	0.091	0.287
ONEWAY	1 if the roadway is a one-way road; 0 otherwise	0.070	0.254	0.050	0.217
STRAIGHT	1 if the roadway is straight; 0 otherwise	Base variable for horizontal curve			
CURVRIGHT	1 if the roadway curves right; 0 otherwise	0.161	0.367	0.060	0.237
CURVLEFT	1 if the roadway curves left; 0 otherwise	0.266	0.442	0.052	0.222
LEVEL	1 if the roadway is level; 0 otherwise	Base variable for grade			
UPHILL	1 if the roadway is uphill; 0 otherwise	0.152	0.359	0.171	0.377
DOWNHILL	1 if the roadway is downhill; 0 otherwise	0.303	0.460	0.144	0.351
Occupant Characteristics					
#AGE	Occupant age, in year	27.856	15.952	31.910	18.924
MALE	1 if male; 0 otherwise	Base variable for gender			
FEMALE	1 if female; 0 otherwise	0.384	0.486	0.514	0.500
FRONTLEFT	1 if seated in the driver seat (front left); 0 otherwise	Base variable for seat position			
FRONTRIGHT	1 if seated in the front passenger seat (front right); 0 otherwise	0.208	0.406	0.202	0.401
SECONDLEFT	1 if seated in the second row, left seat; 0 otherwise	0.076	0.264	0.081	0.272
SECONDRIGHT	1 if seated in the second row, middle or right seat; 0 otherwise	0.066	0.249	0.048	0.214
OTHERPOSITION	1 if seated in position other than the above and front left; 0 otherwise (including the third row and outside the pickups)	0.008	0.091	0.010	0.102
Crash Information					
OTHERIMPACT	1 if the vehicle angle impact other vehicles (or object, for one-vehicle crashes); 0 otherwise	Base variable for crash type			
HEADON	1 if the vehicle crash head-on (or with front end, for one-vehicle crashes); 0 otherwise	0.094	0.291	0.462	0.499
REAREND	1 if the vehicle crash with its rear end; 0 otherwise	0.006	0.076	0.098	0.297
LEFTSIDE	1 if the vehicle is impacted on its left side; 0 otherwise	0.332	0.471	0.190	0.393
RIGHTSIDE	1 if the vehicle is impacted on its right side; 0 otherwise	0.549	0.498	0.169	0.374

* This variable is also used in the heteroscedasticity specification of two-vehicle crashes.
# This variable is also used in the heteroscedasticity specifications of two-vehicle and one-vehicle crashes.

Table 4-30 – Ordered Logit and Heteroscedastic Ordered Logit Regression Models of Injury Severity – NASS CDS Data

Variable	One-vehicle Crashes				Two-vehicle Crashes			
	HOL		OL		HOL		OL	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Latent injury severity measure								
Constant	-1.257	-28.144	-2.003	-25.287	12.413	90.678	2.532	64.278
CURBWGT	0.039	17.478	0.038	9.905	-0.614	-135.635	-0.156	-92.983
CURBWGTSQD	-4.42E-04	-13.745	-3.87E-04	-7.032	7.27E-03	132.061	1.81E-03	77.166
VEHAGE	-8.78E-03	-25.449	-1.47E-02	-23.688	6.87E-02	49.261	1.86E-02	50.019
MINIVAN	-0.016	-0.418	0.204	3.591	0.967	29.696	0.327	41.795
SUV	-0.180	-43.351	-0.233	-31.328	0.916	35.100	0.321	46.125
PICKUP	0.134	14.792	0.399	24.678	-0.057	-1.753	0.085	11.271
PNVEHWGT	---	---	---	---	0.027	5.888	0.026	32.190
PNVEHWGTSQR	---	---	---	---	2.79E-04	4.503	-1.74E-04	-18.109
PNSUV	---	---	---	---	1.048	55.575	0.258	47.445
PNMINIVAN	---	---	---	---	0.535	26.467	0.084	13.061
PNPICKUP	---	---	---	---	0.400	24.668	0.247	61.330
PNMDTHDT	---	---	---	---	-23.010	-8.076	5.186	12.177
FOLDINGBUCKET	0.077	20.112	0.130	18.270	-0.363	-28.260	-0.130	-35.419
BENCHSEAT	-0.198	-19.462	-0.396	-21.163	0.082	1.989	0.066	6.362
SEPBENCH	0.214	27.583	0.405	27.795	1.475	56.098	0.448	65.532
FOLDINGBENCH	-0.183	-20.939	-0.281	-17.518	-0.437	-13.074	-0.123	-14.306
OTHERSEAT	-0.109	-2.510	-0.271	-4.303	-0.023	-0.470	-0.019	-1.614
LAPSHOU	-0.728	-204.374	-1.320	-211.569	-2.160	-133.069	-0.627	-141.222
OTHEBELT	-0.530	-135.598	-0.953	-135.285	-2.464	-146.551	-0.687	-144.914
BADWEATHER	-0.487	-94.221	-0.923	-99.753	-1.539	-117.098	-0.397	-116.589
DARK	-0.044	-14.733	-0.061	-11.013	0.714	50.964	0.214	55.364
SPDLIMIT	2.75E-02	45.976	5.62E-02	50.903	-1.76E-01	-45.570	-3.52E-02	-33.491
SPDLIMITSQD	-2.16E-04	-32.746	-4.27E-04	-35.555	2.62E-03	56.719	6.23E-04	50.764
NONPOSITIVEDIV	0.283	49.693	0.510	48.301	-0.287	-21.877	-0.078	-21.339
POSITIVEDIV	-0.045	-7.380	-0.123	-11.308	-2.486	-106.320	-0.733	-116.048
ONEWAY	0.167	22.520	0.220	16.245	-0.648	-19.070	-0.240	-27.043
CURVRIGHT	0.169	30.310	0.225	22.272	1.177	46.756	0.359	56.700
CURVLEFT	0.257	59.929	0.446	57.642	1.815	72.514	0.516	82.097
UPHILL	0.051	8.743	0.097	9.008	-0.546	-34.548	-0.141	-33.562
DOWNHILL	-0.084	-18.375	-0.136	-15.999	1.111	58.967	0.300	60.230
AGE	8.85E-03	75.534	1.65E-02	75.763	2.39E-02	63.381	7.20E-03	75.162
FEMALE	0.315	131.189	0.604	137.466	1.223	110.979	0.331	108.757
FRONTRIGHT	-0.094	-49.763	-0.164	-48.749	0.115	9.844	0.012	3.643
SECONDLEFT	-0.376	-42.366	-0.697	-42.843	-1.587	-40.238	-0.438	-43.700
SECONDRIGHT	-0.362	-40.971	-0.680	-41.975	-1.655	-30.764	-0.491	-36.499
OTHERPOSITION	-0.093	-1.224	-0.159	-1.533	-0.950	-14.921	-0.060	-3.543
HEADON	-0.352	-19.637	-0.632	-19.486	-0.561	-22.059	-0.197	-28.856
REAREND	0.266	2.148	0.590	2.258	-1.067	-33.997	-0.320	-38.966
LEFTSIDE	-0.129	-7.222	-0.140	-4.341	-0.987	-36.935	-0.299	-42.057
RIGHTSIDE	-0.043	-2.398	-0.026	-0.781	-0.648	-24.467	-0.171	-24.703

Results of Ordered Logit and Heteroscedastic Ordered Logit Models (Cont'd)

Variable	One-vehicle Crashes				Two-vehicle Crashes			
	HOL		OL		HOL		OL	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Latent injury severity measure variance								
AGE	-2.55E-03	-2.815	---	---	4.48E-04	0.827	---	---
VEHAGE	3.06E-03	1.119	---	---	5.26E-03	2.556	---	---
CURBWGT	-4.77E-02	-7.726	---	---	5.81E-02	13.945	---	---
CURBWGTSQD	6.18E-04	6.703	---	---	-7.91E-04	-16.608	---	---
MINIVAN	0.323	3.973	---	---	7.29E-04	0.017	---	---
SUV	0.134	2.825	---	---	7.00E-03	0.172	---	---
PICKUP	0.298	5.511	---	---	0.153	3.609	---	---
SPDLIMIT	8.12E-03	1.692	---	---	6.53E-03	1.536	---	---
SPDLIMITSQD	-6.06E-05	-1.154	---	---	1.06E-05	0.210	---	---
PARTNERVEHWGT	---	---	---	---	-4.80E-03	-1.068	---	---
PNVEHWGTSQD	---	---	---	---	6.87E-05	1.194	---	---
PNSUV	---	---	---	---	-5.04E-02	-1.509	---	---
PNMINIVAN	---	---	---	---	-0.125	-3.235	---	---
PNPICKUP	---	---	---	---	0.256	7.810	---	---
PNMDTHDT	---	---	---	---	-2.931	-1.117	---	---
Thresholds								
μ_0	0.000	---	0.000	---	0.000	---	0.000	---
μ_1	0.356	23.699	0.650	34.465	4.214	30.234	1.143	71.598
μ_2	1.058	28.502	1.926	54.505	7.835	30.974	2.102	84.575
μ_3	2.595	25.975	4.659	41.637	21.331	26.034	5.406	45.741
Nobs.	7,564				19,056			
LRI	0.241		0.238		0.262		0.256	

Table 4-31 – Effect of Speed Limit on Occupant Injury Severity – NASS CDS Data

Speed Limit Before Change	Speed Limit After Change	Percentage Change in Probability				
		No Injury	Possible Injury	Non-incapacitating Injury	Incapacitating Injury	Fatality
55 mi/h	70 mi/h	-17.2	-2.0	16.3	55.2	110
60 mi/h	70 mi/h	-12.4	-2.4	9.9	34.5	67.6
65 mi/h	70 mi/h	-6.7	-1.8	4.3	16.1	31.0

Note: Probabilities are calculated while evaluating all other variables at their weighted average values.

4.5 Summary of Analysis Results

As the chapter makes clear, the project undertook a large number of traffic safety analyses using a broad range of methods and drawing on a wide variety of data sources. This section summarizes the main technical conclusions regarding the work results, and relates these back to the general framework (described in section 4.1) that guided the development and pursuit of the project's research strategy.

4.5.1 Speed Choice Models

These models were intended to illuminate the relationships between speed limits and driver speed choices, as these are reflected in average vehicle speeds and speed variability.

The initial analyses of average speed and speed variability used data from traffic detectors in northwest Washington State (Appendix D). Recall that the traffic detector data used in these analyses were only available at five-minute time aggregations, and that an extensive set of assumptions had to be made in order to develop measures of speed variance from it. In addition, the highway characteristics at all the detector sites were quite similar, making it difficult to identify the effect of specific highway features on speed choice. Because of these factors and perhaps others, the estimated speed choice models proved to be unreliable: application of the model resulted in speed predictions of under 40 mi/h or over 80 mi/h at many sites.

The ARIMA intervention analyses of speed limit changes in Washington State (section 4.2.4) had the advantage of being able to use data that included actual (rather than estimated) vehicle speed measurements, although these were accumulated to produce average hourly values. It was based on a comparison of four sites, including two urban and two rural, as well as two that experienced speed limit changes and two that did not. The analysis showed that a 5 mi/h speed limit increase at two sites had the effect of raising average speeds there by around 2 mi/h, and raising the speed variance by significant but different amounts at the two sites. Over the same period, the sites that did not experience a speed limit change exhibited essentially no changes in their traffic speed characteristics. Due to the small sample size, however, it is difficult to justify the application of these results more generally.

Analyses of the Southern California crash and traffic datasets compiled by Golob and Recker (section 4.2.2) were useful in highlighting basic design, environmental and traffic factors that correlate with freeway section traffic speed characteristics (average speed and speed variance) within and between lanes. However, since all of the analyzed sections had a 65 mi/h posted speed limit, the analysis was not able to identify the effect of different speed limits on traffic speed characteristics.

The analysis of individual vehicle speed data obtained from a small cross-section dataset of radar gun speed measurements on roadways in Austin, Texas (section 4.2.3). This was the only source of individual vehicle speed data available to the project. The analysis identified a number of engineering, environmental and traffic characteristics that influence average speed and speed variance. Comparing different roadway sections in the analysis, it was found that a 10 mi/h difference in speed limits was associated with a roughly 6.5 mi/h difference in average vehicle speeds. A particular highlight of this analysis was its demonstration that the impact of speed limits on vehicle speed variances is, at most, very small. Again, the small sample size limits the broad applicability of these results.

It should also be noted that the analyses mentioned in the preceding two paragraphs did not include any segments on which the speed limit changed during the data collection. This limits the extent to which the results obtained (for fixed speed limits) can be extrapolated to situations involving speed limit changes.

In this regard, it is interesting that the before-after analysis of vehicle speeds on roads that experience a speed limit change suggests a much more moderate response to the change than does a cross-sectional analysis of speeds on roadways with different limits. The before-after analysis of Washington State roadways, for example, suggests that a 10 mi/h speed limit increase is associated with a 3.4 mi/h average speed increase, whereas the cross-sectional analysis of Austin vehicle speed measurements on segments with different speed limits indicates a 6.5 mi/h difference in average speeds on roadways having a 10 mi/h speed limit difference. The prediction from cross-sectional data is roughly twice as high as that obtained from before-after data. Differences in methods of data collection and processing may also account for part of the discrepancy between the two sets of results: the Washington data was available in the form of speed averages computed from PTR measurements, while the Austin data consisted of radar gun measurements of individual vehicle speeds.

4.5.2 Crash Occurrence Models

The results of the project analyses of speed limit effects on crash rates (or counts) suggested only slight impacts. However, these results are not considered to be highly robust.

The original analysis was based on disaggregate HSIS crash data from Washington State (Appendix F). Data on total crashes as well as crashes and injuries by severity were analyzed using a variety of generalizations of the basic Poisson regression model, including negative binomial, zero-inflated Poisson and negative binomial, and fixed and random effects Poisson and negative binomial models. However, none of the estimation results for these models could be considered satisfactory as regards their specification validity, intuitiveness and statistical performance. For this reason, the project's subsequent analyses of crash occurrence models were based on datasets obtained by clustering HSIS segments over several years of data.

The first such analysis estimated fixed and random effects linear regression models of aggregate cluster crash counts against a number of engineering, environmental and traffic use variables (section 4.3.1). This analysis found that, other things equal, the relationship between speed limit and total crash rate is concave, with a maximum around 70 mi/h. (This was the highest observed speed limit, and the model was not extrapolated beyond that value.) However, the effect of speed limits on crashes was weak and, because of the concavity, became even weaker at higher speed limits.

A model of crash count changes was specified and estimated using a dataset of clustered Washington State HSIS segment data over a multi-year period that included the NMSL repeal (section 4.3.2). The results of this analysis were generally consistent with those of the preceding crash count analysis.

4.5.3 Injury Severity Models

Recall that crash and injury severity models apply when crashes have occurred, and are used to estimate the associated distribution of crash or injury severities.

The project used the HSIS data (for Washington State) and the NASS CDS to estimate ordered logit models of injury severity (sections 4.4.1 and 4.4.2). Both models are consistent in that they predict sizeable percentage increases in the rates of incapacitating and fatal injuries following a 10 mi/h or higher speed limit increase. However, the magnitudes of the predicted increases are quite different. For typical speed limit increases, the model developed from Washington State data on high speed roads predicts an increase in fatalities in the range of 7%-39%, while the model estimated from NASS CDS data on all roads predicts increases in the range of 31%-110%.

Of the two models, it is likely that the one developed from Washington State HSIS data is more applicable to the analysis of speed change impacts on high-speed roads because the estimation dataset contained only data on such roads. In contrast, the NASS CDS dataset included observations from roads of all types, and data on lower-speed roads may influence model results for high-speed roads, exaggerating the predicted impact of speed limit changes on them.

It should also be noted that predictions of injury severity distribution changes following speed limit changes, such as those mentioned above and shown in Tables Table 4-27and Table 4-31, require the application of both speed choice models and injury severity models. The speed choice model was based on cross-sectional data and, as was discussed above, it seems that models estimated from such data may tend to overestimate the speed change impact by a factor of roughly 2 when compared to the results of actual before-after studies on individual roadways. This implies that the predictions of injury severity changes following a speed limit change may be based on estimated average speed differences that are too high. This would, of course, also result in an overestimate of the injury severity impact, perhaps by a factor of more than 2.

Focusing on the HSIS-based model, it is natural to ask how its predictions of fatality rate changes following speed limit increases compare with actual experience following the NMSL relaxation and repeal. As has been stressed repeatedly in this report, comparison of aggregate crash statistics is an unreliable method of assessing speed limit change impacts because of the large number of other factors that can (and frequently do) differ between the statistics being compared. This explains why the results of such studies have frequently been inconclusive or contradictory, as discussed in the Chapter 2 literature review.

However, it is nonetheless interesting to note that a few studies have found significant increases in fatality rates on high-speed roads following the NMSL relaxation from 55 to 65 mi/h on rural interstates. Using Illinois data, Rock (1995) identified a 40% increase in fatalities on rural highways. Ledolter and Chan’s (1996) similar work with quarterly Iowa data from 1983 to 1991 estimated a 57% increase in fatal crashes on rural interstate highways following the speed limit increase. Brownstone (2002), considering national state-level data by highway type, found that fatality rates on rural interstates increased by 30% following the NMSL relaxation.

The corresponding prediction of the HSIS-based model is 24%. Strictly speaking, these values cannot validly be compared, but it is striking that, although the value that we found is slightly lower than those found in the research cited here, these results are all in the same general range. While this is definitely not a validation of the HSIS-based model, it is fair to say that its predictions are roughly consistent with the NMSL relaxation fatality impacts found by the researchers cited above.

5 Summary, Conclusions and Recommendations

5.1 Safety and Operational Impacts of Speed Limit Changes

5.1.1 Summary Results

This project carried out a considerable number of analyses of the effects of speed limits and other factors on speed choice, crash incidence and crash severity. The analyses drew on a variety data types including loop detector measurements, stated preference surveys, revealed choices, and crash records containing information about crash counts and severities, vehicles and their occupants, and roadways and their environments. The project made extensive use of data obtained from Washington State because of its quality and the effort required to assemble a useful dataset from disparate original sources. However, data from a national driver safety survey, vehicle speed data from Southern California and Austin, Texas, and a national sample of crash records were also used. The analyses applied state-of-the-art statistical methods to address a number of data features that complicate traffic safety analyses. The project's datasets and analyses are thoroughly described in Chapter 4 of this report.

As explained in Chapter 4, the project's research strategy was based on a high-level framework encompassing the relationships between driver speed choice behavior, crash occurrence and injury or crash severity. The project analyses led to the development of various quantitative models of these relationships, and the various datasets mentioned above were then used to estimate them. The data generally dictated the most appropriate methods for their analysis; these methods ranged from ARIMA models (of speed data over time) to weighted least squares regression (of crash counts for road segments clustered on the basis of design attributes), and from random-effects negative binomial models (of crash counts on short roadway segments each year) to heteroscedastic ordered logit models (for crash and injury severity).

Although the data did not permit estimation of models that directly link crash counts and severity to actual speed choices[39], the results do suggest how speed limits and roadway design and use, along with other control factors, may affect speed choice, crash frequency, and crash severity. Based on these analyses, a number of relatively simple conclusions can be drawn:

- A speed limit increase tends to be associated with higher average vehicle speeds. The average vehicle speed rises by less than half of the amount of the speed limit increase itself.
- Our predictions of the average speed increase associated with a speed limit increase may be overestimated because our models were based on cross-sectional data rather than actual before-after observations.

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[39] As discussed later in section 5.4, relatively few network sites offer reliable dual-loop detector stations for accurate recording of speed information. Most sites are urban in nature, and many are missing data. In addition, all aggregate their speed data temporally (e.g., to 5-minute intervals), losing valuable information on instantaneous variations in speed choice. The models of speed choice that were developed from the small subset of Washington State sites having such detectors performed very poorly in prediction. Ideally, one would like to have actual speed data for all sites used to calibrate models of crash frequency (and severity). Such a dataset is not yet available for sufficient sites.

- If a roadway's design speed (or "safe speed") is also increased, simulations of hypothetical driver behavior suggest that driver optimal speed choices rise by roughly the full amount of the design speed change (assuming that speed limits and design speeds rise together).
- Average speed and speed variability tend to reflect highway design and use characteristics more than they reflect speed limits. In fact, after controlling for these other characteristics, variations in observed speed choices seem largely unaffected by speed limits (and by changes in speed limits).
- Total crash counts tend to increase with speed limit increases, but not dramatically: other things equal, a 10 mi/h speed limit increase on a typical high-speed roadway can be expected to lead to a roughly 3% increase in total crash counts.
- Roadway features other than speed limit also affect the total crash rate. Sharper horizontal curves and steeper vertical grades are associated with higher rates. Roadways with medians tend to exhibit lower crash rates, as do those with wider shoulders. Other things equal, roads with 4-5 lanes tend to have higher crash rates than those with other numbers of lanes.
- Using flexible models of crash severity, estimated using occupant-level data, the project found an unambiguous association between speed limit increases and the distribution of crash severity. Models developed from Washington State and national databases both suggest that higher speed limits lead to a significant increase in the proportions of severe injuries and fatalities. However, the models differ (by a factor of approximately 2) in their predictions of the magnitude of these increases.
- Because the HSIS-based injury severity model was estimated using only data on high-speed roads, it is felt to be more applicable. For a speed limit increase from 55 to 65 mi/h, the increases in fatal injuries predicted by this model are on the order of 28%; the specific magnitude depends on occupant and roadway characteristics.
- The value of this predicted increase in fatalities is roughly consistent with the increases in fatality rates found by several researchers on rural interstates following the 1987 NMSL relaxation. However, this approximate correspondence does not constitute a validation of the HSIS-based model, and it must also be noted that other researchers have found smaller (or no) changes in fatality rates following the NMSL relaxation and repeal. Typically, such work has relied on more aggregate data, using statistical methods less able to exploit data characteristics, and a following a less comprehensive approach than were used here.
- Since injury severity and related predictions derive here from cross-sectional models, they will be tend to be overestimated if actual speed differences are higher than those that are estimated following changes in the speed limit.

Strictly speaking, these conclusions apply only to the specific datasets that were analyzed and the particular geographic areas from which their data were collected. (The analyses of Washington State HSIS data were especially important in developing many of the conclusions regarding crash incidence.) However, insofar as there is nothing particularly distinctive or unusual regarding the highway, environmental, vehicle or driver characteristics in the geographic areas that provided the data for these analyses, one may consider these conclusions to be more broadly applicable. In any case, considering the effort and time that were required to assemble and analyze these datasets, it was not feasible for the project to attempt a comparably detailed research effort over a wider geographic scope. (This point is discussed further below.) National data were used for the severity model inferences, and these are consistent with the Washington State severity model results.

5.1.2 Detailed Results

The high-level conclusions listed above are derived from and supported by detailed results from the many analyses of speed and crash data that the project carried out. The main analyses and their results are briefly summarized in the following paragraphs. Again, Chapter 4 describes these in detail, while some of the project's secondary analyses are presented in the various Appendices to this report.

5.1.2.1 Speed Choice Models

Highway Driving Speeds Reported in the MVOSS

The project analyzed results from the 2000 Motor Vehicle Occupant Survey (MVOSS), a nationwide telephone survey of roughly 6,000 persons aged 16 or over. The survey questions emphasized traffic safety issues, including crash exposure, travel choices (such as usual driving speed, driving frequency and seatbelt use), and attitudes towards driving and current speed limits. Basic demographic information about the respondent, and about the type of vehicle usually driven, was also obtained. The project's analysis highlighted the intrinsic variability in speed choices across drivers, particularly under relatively uncongested conditions. For example, other things equal, males tend to report driving highways at speeds that are almost 1 mi/h faster than females, college-educated persons 1.6 mi/h faster (than those without college educations), and persons living in central cities/urban areas about 1.3 mi/h faster than rural residents. For every $50,000 rise in household income, drivers report driving about 2 mi/h faster, while those typically driving SUVs report driving 1.6 mi/h slower on average.

Speed Choice on Orange County Freeways

Variation in speed choices also reflects highway design attributes and environmental conditions. Using 30-sec loop detector data from freeways in Orange County, California in 1998, within-lane average speeds (Table 4-6) were estimated to rise almost 4 mi/h as the number of lanes (in one direction) went from 3 to 5 or more, and by 6.2 mi/h as design speeds rose 10 mi/h. Average section speeds (Table 4-9) were predicted to fall almost 5 mi/h under wet conditions, 4.8 mi/h at nighttime when lighting is provided, and another 3.5 mi/h when lighting is not provided. There is also great variation in average lane speeds across lanes (Table 4-6), with inside lanes averaging 6.2 to 7.3 mi/h more than right-side lanes, and 1.7 mi/h more than the next-to-inside lane. Of course, traffic intensity also has a significant effect, suggesting a reduction of 0.62 mi/h in average lane speed for every added vehicle per lane mile (Table 4-6), or 0.71 mi/h in average section speed (Table 4-9).

Estimates of the standard deviation of between-vehicle speeds in the Orange County dataset (based on variations in successive average speed values) suggested that increases in design speed and average speed contribute in minor ways to speed variability. For example, within-lane speed standard deviation (Table 4-5) is predicted to rise 1.39 mi/h with a 10 mi/h increase in design speed, and another 0.46 mi/h with a 10 mi/h increase in the average (within-lane) travel speed. Darkness, wet pavements, obstructions and construction also raise within-lane speed variability.

Inside lanes exhibit substantially less variation than their right-side counterparts, and congestion or traffic intensity also is a key factor. Total variations in average speeds across and within lanes oppose many of these effects (Table 4-8), resulting in net effects on total-segment speed variation of 1.8 mi/h following a 10 mi/h increase in design speed, and 0.78 mi/h following a 10 mi/h rise in average section speed.

As was expected, predicting traffic speeds is easier than predicting variations in these speeds. The R2 goodness-of-fit values of the Orange County regression models of average speeds were 0.59 or higher (Tables 4-6 and 4-9), while those for models of speed standard deviation (within and across lanes) ranged from 0.12 to 0.41 (Tables 4-5, 4-7, and 4-8).

Individual Vehicle Speed Choice in Austin, Texas

To complement the analyses based on datasets of aggregate vehicle speeds, a limited set of observations of individual vehicle speeds was collected using a radar gun on a variety of high-speed highways in Austin, Texas. Weighted least squares models were developed to assess the effects of flow, number of lanes and other variables on the average and standard error of individual vehicle speeds. This was the only dataset containing individual vehicle speed measurements that was available to the project.

The final model of average vehicle speed included five statistically significant explanatory variables: pavement dry/wet condition, presence of a downstream intersection within 0.25 mile, equivalent hourly lane flow volume, speed limit, and facility access control (Table 4-11). Other things equal, a 5 mi/h increase in speed limit is estimated to result in a roughly 3.4 mi/h increase in average vehicle speed. Facility access control results in a 4 mi/h increase, while wet pavement conditions result in a 3 mi/h decrease in average speeds. Higher flow rates and the presence of a nearby downstream intersection both reduce the average vehicle speed. The adjusted R2 was 0.64, which appears quite satisfactory but may be biased upwards since the least squares assumption of independent error terms is violated by the repeated observations taken with the radar gun.

The final model of speed standard error had a minimal goodness of fit (adjusted R2 of 0.01). Estimation results suggest that a 5 mi/h increase in the speed limit reduces vehicle speed standard error by 0.1 mi/h. Other things equal, vehicle speed variations are higher on access controlled freeways, rural facilities, those with more lanes, and near a downstream intersection.

Speed Limit Change Intervention Analysis in Washington State

WSDOT's system of permanent traffic recorders (PTRs) provided hourly vehicle counts by speed for four sites from 1995 through 1997. These sites reflect combinations of urban and rural locations, with and without a speed limit increase (of 5 mi/h). ARIMA intervention analysis (Table 4-15) suggests that the 5 mi/h speed limit increase at two of the sites was associated with an average speed increase in the range of 1.2-1.6 mi/h. Speed variance at the rural site increased by roughly 5 mi^2/h^2, but there was no statistically significant speed variance change at the urban site. Urban congestion may be one reason for these different results. The sites with no speed limit change exhibited practically no change in speed or speed variance.

Analysis of Rational Speed Choice Using Simulated Data

The project also developed a theoretical model of how rational drivers choose their driving speeds, in order to minimize a generalized cost of travel, based on a highly non-linear formulation. Optimal speeds were found for a wide range of plausible parameter values, and linear regression models were developed to relate the optimal speeds that were developed from this procedure to the key explanatory variables (Table 4-17). It was found that a 10 mi/h speed limit increase results in an increase in chosen speed of between 3.7 and 4.4 mi/h, which is very consistent with actual, observed speed changes. Moreover, estimation results suggested that "safe" speeds (for which design speeds may be a reasonable proxy) are more important in determining actual speed choice than are speed limits. However, these two variables do appear to complement each other: a simultaneous increase of 1 mi/h in both speeds results in an almost identical increase in the chosen speed.

5.1.2.2 Crash Occurrence Models

The analysis used HSIS data for Washington State, covering the years 1993-1996 and 1999-2002. Segments were manually clustered on the basis of design details, resulting in a panel of relatively homogeneous clusters. Linear random effects models of total crash counts (all severities combined) were statistically preferred to fixed-effects models (Table 4-20). Crash counts were predicted to rise in a concave, quadratic fashion with speed limits. It was predicted that 3.29% more crashes would occur if speed limits were to increase from 55 mi/h to 65 mi/h on an "average" roadway section. This number fell slightly (to 2.90%) when the data were examined using a before-after regression. This approach reduced the dataset size (per cluster) significantly, but was pursued in order to remove the potential for omitted-variables biases in the speed limit coefficients. In both models it was found that speed limits, right shoulder width, degree of horizontal curvature and the presence of a median were the most important factors affecting crash frequency.

5.1.2.3 Crash Severity Models

Crash severity models are concerned with predicting the distribution of injuries by severity, given that a crash has already occurred. Heteroscedastic ordered logit models were estimated, using regional and national datasets. These offered similar results and conclusions.

The first model used Washington State HSIS data from 1993 through 1996 for high-speed roadways. The second pair of models relied on a national database (the NASS CDS) of vehicle and crash data from 1998 through 2001, covering all roadway types (not just high-speed roads). This pair of models distinguished single-vehicle from multi-vehicle crashes. All models were based on five injury severity levels for occupants. While the Washington model offered more information on crash site characteristics, the national database contained information on vehicle weight, a potentially key variable that is changing over time.

Results from both models suggest that roadways with higher speed limits experience significantly higher fatality rates (Tables Table 4-26 and Table 4-30) – everything else constant (including design and use attributes). This occurs primarily through increases in the (predicted) variance of the model's latent error term, but also through increases in the general, latent severity level – particularly in the case of multi-vehicle crashes (as examined with the national database). However, the models differ considerably in their estimates of the magnitude of these impacts; the NASS CDS-based model estimates fatality increases roughly twice as large as those of the HSIS-based model.

The statistical association between the probability of fatal injury and speed limit has a concave form. Since actual, practical speed limits lie below the speed limit associated with the highest fatal injury probability, the increase in fatal injury probability tapers with increases in speed limits. This may occur due to a compensation effect, where drivers drive more carefully at higher speeds. It also may be due to a threshold or saturation effect (where drivers and their vehicles are not willing or able to travel any faster), or to latent variable effects (such as the highest-speed roadways occurring only in the safest driving environments.)

The HSIS-based model is felt to be more applicable to the analysis of the impacts of speed limit changes on high-speed roads, because it was estimated using only data from such roads. It is likely that the predictions of the NASS CDS-based model for high-speed roads are unduly affected by its observations for lower-speed facilities.

Focusing on the HSIS-based model, the probability of sustaining a fatal injury following a crash is estimated to rise by 24% if the speed limit increases from 55 to 65 mi/h, and by 12% if the increase is from 65 to 75 mi/h. Other predictions can be found in Table 4-27. However, to the extent that actual speed choices do not rise as much following a speed limit change as they appear to do in cross-sectional databases, these severity results may be overestimated.

The predicted increase is roughly consistent with the increase in fatalities on rural interstates found by several researchers (Rock, 1995; Ledolter and Chan, 1996; Brownstone, 2002) in their analyses of the 1987 NMSL relaxation. However, this cannot be considered a "validation" of the HSIS-based model because of the many difficulties associated with prior works' analysis of aggregate crash statistics, due to the effects of multiple confounding changes (such as route changes). Moreover, other researchers conducting aggregate analyses of the NMSL relaxation and repeal have found small or no fatality rate impacts.

5.2 Non-Safety Impacts of Speed Limit Changes

The project also examined non-safety impacts associated with speed limit changes; this was, however, a lower priority activity than investigating their safety impacts. The examination was based in part on a review of the relevant technical literature, as well as on survey responses received from state DOTs. Some state DOTs carried out studies of impacts of the NMSL repeal, and some of these studies included qualitative consideration of such non-safety factors. Available reports from these studies were obtained and reviewed as well for information on non-safety impacts.

In broad terms, non-safety impacts of speed limit changes may include effects on economic, environmental and/or commercial conditions. Unfortunately, generally applicable conclusions regarding such effects are mostly lacking.

Speed limit increases translate into less-than-equivalent increases in average travel speed. The project found, for example, that a 10 mi/h speed limit increase would result in average travel speeds roughly 4 mi/h higher, provided that other factors such as congestion did not constrain travel speeds. The reduced travel times made possible by higher travel speeds have an economic value. US DOT (1997, 2003) guidelines, for example, suggest that the travel time of intercity passengers on surface modes should be valued at approximately $15/h on average. When considering the system-wide impacts of a speed limit change, it must be remembered that not all trips will be fully affected by the change. For example, trips for which the average speed is significantly constrained by congestion will not experience the full effect of a speed limit change whereas those less affected by congestion are likely to experience greater impacts. Moreover, to the extent that higher speeds translate into a slightly higher crash rate (the project found that a 10 mi/h speed limit increase would result in a crash rate increase of roughly 3%), the travel delays resulting from crashes (known as non-recurrent congestion) will also increase, offsetting somewhat the reduction in travel times made possible by higher average speeds. Finally, travel time reliability also has an intrinsic economic value (Small *et al.*, 1999), and the reduced time reliability resulting from slightly higher crash rates at higher speeds would also offset to some extent the economic value of the lower travel times.

Changes in average travel speed also affect vehicle operating costs. Of the various cost components that contribute to overall operating costs, running costs (those that directly result from vehicle operation) are most significantly impacted by speed; and of running cost components, fuel consumption costs are the largest portion. For a medium or large car, fuel consumption at 55 and 65 mi/h calculated using the FHWA's HERS-ST model (FHWA, 2002) with an economic fuel cost of $1.50/gallon[40] shows that the 4 mi/h average speed increase noted above would lead to an operating cost increase that is roughly half the estimated value of travel time savings. Thus, the net (time and cost-related) benefit resulting from higher average speed is further reduced.

The project reviewed the two main approaches used to quantifying the economic costs of injuries and fatalities: the human capital approach, and the willingness-to-pay approach.

With respect to the environmental impacts of speed limit changes, the little evidence available suggests that these are small to negligible.

The noise impacts of post-NMSL speed limit increases were modeled in New Jersey using actual before-after speeds and traffic volumes on affected facilities. It was concluded that the change in noise level would be imperceptible in the noise environment on and surrounding the roadways.

Air quality issues have been evoked in some locations as a reason for lowering speed limits. (These are sometimes called environmental speed limits.) In the Houston-Galveston (Texas) area, for example, preliminary modeling analysis of a proposal to reduce speed limits on high-

[40] $2/gallon pump price minus $0.50/gallon transfer payments such as Federal and state taxes.

speed roads suggested that such limits would improve compliance with EPA air quality standards. Opposition to this suggestion led to an analysis using a more up-to-date air quality model that predicted a much smaller change in air quality from a speed limit reduction, and the proposal was suspended. The New Jersey study mentioned in the preceding paragraph also investigated air quality changes resulting from the higher speed limits, and found these to be "nominal" (i.e. insignificant).

The project was unable to find any empirical or documentary evidence regarding possible commercial impacts of speed limit increases. The resulting (smaller) increases in average speeds of commercial vehicles should, in the medium to long term, result in opportunities for more efficient transportation and business operations. However, such speed changes are typically small, and the productivity of a commercial vehicle (and of the operations that it serves) depends only partly on its travel speed since it may spend significant time in loading/unloading operations or waiting for cargo. Thus, the impacts on business and commerce of speed limit changes are likely to be marginal.

5.3 Enforcement Policy Responses to the NMSL and its Repeal

Institutional memory concerning the specific decisions that were taken by DOTs and state police agencies at the time of the large-scale speed limit changes is beginning to be lost. Many of the personnel who were involved in developing high level policies and strategies to respond to the NMSL imposition, relaxation and repeal were, at that time, in relatively senior positions. Many of these officials are no longer accessible. Consequently, much the detailed information about the policy and strategy responses of DOTs and State Police, and about how these responses were developed, is now either unavailable or only anecdotal in nature.

It is sometimes claimed that the NMSL imposition and related Federal mandates led to a systematic concentration of speed limit enforcement efforts on high-speed roads, to the detriment of potentially more beneficial traffic enforcement efforts of other kinds or on other facility types. Available data from DOTs and state police agencies do not allow a rigorous investigation of this assertion. Similarly, available data do not allow a rigorous investigation of the converse hypothesis, namely that the NMSL relaxation and repeal were accompanied by a widespread redeployment of enforcement resources away from speed enforcement on high-speed roads and towards other activities with potentially higher traffic safety benefits. Nonetheless, anecdotal evidence collected by the project through surveys of state DOT and police officials across the country does suggest that neither of these things happened systematically or on a large scale.

Some respondents acknowledged that there was a concern to demonstrate compliance with the NMSL in order to avoid Federal sanctions. However, respondents were adamant that no enforcement actions taken during the period of the NMSL were of a nature to compromise traffic safety. Similarly, respondents cited no examples of systematic changes in enforcement practices away from speed limit enforcement on high-speed roads following the NMSL relaxation and repeal. Indeed, several respondents and DOT reports noted that speed limit enforcement activities actually became *more* intensive on high-speed roads in the period following the repeal, out of concern that drivers who formerly ignored the 55 mi/h limit might continue their scofflaw habits at the higher speed limit, with potentially more dangerous consequences.

The evidence suggests instead that the response of most police agencies to the NMSL relaxation and repeal generally took more measured forms: for example, reduced tolerance for speeds higher than the new limits together with, in some cases, a new speeding fine structure and/or an aggressive information campaign to notify the public of the tougher post-repeal policy.

5.4 Data Recommendations

The methods used in this work were guided, and limited, by the extent and quality of existing datasets. For example, Washington State's HSIS dataset is felt to be the best that the U.S. presently offers, but its panel datasets are missing key years (1997 and 1998). The dual-loop detectors in Washington State's northwest region were originally thought to provide speed averages at 30-second intervals, but it was found that the original detailed data had been lost through aggregation to 5-minute intervals.

Although the characteristics of the available data frequently constrained the types of analyses that the project could perform, the datasets that were assembled and used by the project were typically of a quality higher than (and at least comparable to) those that are generally available elsewhere in the U.S. and abroad. Thus, the data limitations present in the project datasets are likely also to be present in all but very specialized and focused traffic and crash datasets available elsewhere. Broadly speaking, datasets covering extensive geographic areas are likely to be less detailed, while those that include very detailed data are likely to focus on relatively limited geographic areas, highway facilities and/or time periods.

The ideal dataset for traffic safety research purposes would offer true counts and speeds, fully integrated data on design, operations and crashes for a wide range of sites (on the order of at least 500 centerline miles, rural and urban), over several years, both before and after speed limit changes. Exposure (VMT) would be accurately estimated, rather than derived from very imprecise estimates of AADT based on a sparse set of periodic (i.e. occasional) short-term traffic counts, as is frequently the case.

Towards this goal, the project has a number of recommendations regarding future data collection efforts to support fundamental research into crash causality and characteristics, but these recommendations are conditioned by the considerations expressed above. Research-oriented data collection efforts should, as much as possible, complement and build on the crash, traffic, and highway inventory data collection efforts routinely carried out. Given these sources of currently available data, it is worthwhile to focus research-oriented data collection in a few specific ways. These recommendations echo and parallel those of a recent government review of the NHTSA grant program that helps states improve their safety data systems (GAO 2004).

First, traffic safety research would benefit from the collection and assembly of additional *types* of information on the characteristics of roadways and their environments. This could include information on pavement and weather conditions; the presence and nature of embankments, barriers and culverts; driveway and cross-road frequencies; clear zone width; and sight distances. None of the datasets that the project analyzed contained such data. As explained in Chapter 4, one of the analytical difficulties that had to be confronted was the potential for correlations between speed limits and unobserved roadway and environmental characteristics such as these. As discussed in the report, such correlations can bias speed limit impact estimates by attributing to speed limits some of the effects that are actually due to the unobserved characteristics. A dataset containing such data could considerably reduce this difficulty by allowing the effects of these characteristics to be estimated explicitly. However, this work's analysis of crash rate changes resulted in estimates similar to those arising from an analysis of counts (as described in section 4.3), suggesting that this issue may not lead to practically different conclusions.

Second, as a practical matter it would be more efficient to concentrate near term research-oriented data collection efforts on a subsystem of the overall highway system. This would ideally be a subset for which some of the required research-related traffic safety data already exist in some form, and for which the remainder can be expeditiously collected and processed. The high-speed roadway subsystem would seem to be a good initial candidate in this regard. Over the longer term, it would be desirable to extend such data collection efforts to other components of the overall system.

It should be noted that the number of urban areas deploying high-performance traffic sensor systems continues to increase. Such instrumentation and the associated data processing systems can be used to support freeway and/or arterial management systems, incident response systems, and advanced traveler information systems (ATIS), among other uses. The data generated by these traffic measurement systems is frequently preserved and stored; indeed, the on-going Federally-sponsored Archived Data User Service (ADUS) represents a national significant effort to standardize and make available traffic and operations data from traffic sensor systems and other ITS components around the country.

The project examined most of the metropolitan areas with currently operational traffic sensor systems as possible sources of data for its analyses and model development activities. For a variety of reasons, the data from most of the examined systems were found to be unsuitable for project use. Some systems, for example, only covered a relatively small length of roadway, so that the number of crashes occurring on them would be too small to constitute a statistically valid sample. Others aggregated the archived traffic data into time intervals that were too long to be useful for the project's disaggregate analysis of traffic characteristics. In those cases where the data could potentially have been used by the project, the task of assembling and integrating the disparate sources of required data (highway inventory, traffic and crash data) exceeded the resources available to the project. However, it is likely that over time local agencies will find it advantageous to develop and maintain such integrated datasets themselves, and as this happens these will become an increasingly valuable and accessible source of data for traffic safety research.

Towards this end, data producing agencies should be encouraged to adopt consistent geo- or linear referencing systems to facilitate the assembly of integrated sets of disparate data types. Furthermore, agencies should be encouraged to preserve collected data in the most disaggregate form feasible, rather than aggregating it in order to reduce its archiving costs. The declining costs of data storage should make this option more attractive to agencies' data services.

5.5 Overall Conclusions and Recommendations

The NMSL was adopted in 1974 in response to the first energy crisis. Its adoption, together with its relaxation on rural interstate highways in 1987 and its complete repeal in 1995, created the conditions for a unique large-scale natural experiment on speed limits and their safety and other effects. It is not likely that our nation will have another occasion to experience speed limit changes on such a broad scale in the foreseeable future.

It is clear that the more dire predictions that were made about the likely safety impacts of the NMSL relaxation and repeal have not come to pass. Although some researchers have found significant changes in the crash experience of roadways that underwent speed limit changes, others have not, and it is fair to say that a broad consensus as to the effects of the speed limit changes still has not emerged. This suggests that at an aggregate level the overall magnitude of such effects, if indeed they exist, is as small as or smaller than those of changes in a wide variety of other safety-related factors that were occurring at the same time as but (mostly) independently of the speed limit changes themselves. Such changes include, among others:

- variability in weather conditions;
- improvements in roadway design;
- changes in DUI and young driver laws;
- changes in traffic police practices and policies;
- changes in drivers' seatbelt usage habits;
- more effective driver education and public traffic safety awareness programs;
- demographic shifts in the driving population, including driver ages and gender distributions;
- changes in driving patterns, including the distribution of travel between day and night hours, urban and rural locations, and interstate and other facility types;
- improved safety features in vehicle designs;
- increases in VMT per lane mile of network capacity and increases in congestion;
- increased usage of in-vehicle communications devices (e.g. cellular telephones), leading to more rapid notification of and response to crash situations; and
- improved capabilities and effectiveness of emergency response services.

The aggregate combined effects of these changes, together with whatever effects the speed limit increases themselves may have had, appear to have been small.

This project carried out much more detailed disaggregate-level analyses, however, and the conclusions that emerge from these are somewhat clearer.

The project found that small (roughly 3%) increase in total crash rates are associated with a speed limit increase from 55 to 65 mi/h on an "average" high-speed roadway section. It found that a significant increase in the probability of fatalities and incapacitating injuries are associated with higher speed limits. For this particular 10 mi/h speed limit change, a 24% increase in the fatal injury probability would be expected. These predictions would of course be different for different roadway sections and speed limit changes.

Application of the cross-sectional models underlying these crash-severity predictions may tend to over-predict the impacts of speed limit changes because actual changes in average travel speeds following changes in speed limits may be lower than those observed across a set of existing roadways with different speed limits. Nonetheless, even if actual speed changes are expected to be 50% lower than those implied by the cross-sectional models, their impact on the crash fatality rates (and more generally on the injury severity distribution) would in many cases remain statistically and practically significant.

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APPENDICES

Appendix A – Questionnaire Used in Survey of State DOTs
Appendix B – Model of Attitudes Towards Speed Limit Level
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A Questionnaire Used in Survey of State DOTs

Survey of Speed Limits on High-Speed Roads

A Survey of State DOTs Conducted by Charles River Associates

The AASHTO-sponsored National Cooperative Highway Research Program (NCHRP) has recently initiated a project titled "Safety Impacts and Other Implications of Raised Speed Limits on High Speed Roads" (project number 17-23). The objectives of the project are (1) to determine the effects of raised speed limits on high-speed roads; and (2) to develop methods that will assist highway agencies to determine when and where speed limits should be changed. The consulting firm Charles River Associates, in association with Profs. Kara Kockelman and Charles Lave, have been selected to carry out this work.

In this context, **high-speed roads are those with speed limits of 55 mph or greater, including freeways and non-freeways, in both rural and urban environments**. We are particularly interested in speed limit changes made since the National Highway System Designation Act of 1995 repealed the National Maximum Speed Limit (NMSL) and returned to States full authority over speed limits on their roadway systems.

As part of the project, we are conducting a survey to identify and collect data on the experiences of State Departments of Transportation that have raised speed limits. The survey questions are presented below, grouped into sections that deal with related issues. As you will see, some of the questions ask for specific information, while others simply ask you to direct us to a person whom we may contact for more detailed or more voluminous data.

It may be that your Department has already compiled some of the data that we are requesting. If you prefer, you may indicate such cases while filling out the questionnaire, and we will extract the relevant data from reports or studies.

We want to take as little of your time as possible. But your informative responses are very important for the success of this project, so please respond carefully to each question. If there are any aspects of your responses that you would like to remain confidential, please indicate them and we will certainly accommodate your wish.

If you have any questions about this survey, don't hesitate to contact Jon Bottom at jbottom@crai.com or call (617) 425-3392.

Before beginning the survey, please provide your contact information:

Name and Title:

Phone:

Email:

This survey consists of five short sections:

- Section A, Speed Limit Change Data
- Section B, Background Data
- Section C, Speed Limit Enforcement Decisions
- Section D, Speed Limit Change Decisions
- Section E, General Comments

Please respond carefully to all the questions listed under each of these five sections.

A. Speed Limit Change Data

A-1) Did your Department raise posted speed limits on any high-speed road sections following the repeal of the National Maximum Speed Limit (NSML) in 1995?
If so, please provide the *contact information (Name and Title, Phone and Email)* of the relevant person(s) we should contact for information about these changes.

A-2) Has your Department studied the traffic impacts (for example, on speeds, highway safety, volumes and composition, route choice, etc.) of these speed limit changes?
If so, please briefly *describe* the study.
Please also provide the *contact information (Name and Title, Phone and Email)* of the relevant person(s) we should contact to access the study (if it is accessible).

A-3) Has your Department studied other impacts of the speed limit changes? Examples might include impacts on environmental factors (air quality and/or noise), business and commercial activities, or other areas.
If so, please briefly *describe* the study.
Please also provide the *contact information (Name and Title, Phone and Email)* of the relevant person(s) we should contact to access the study (if it is accessible).

A-4) Has your department studied the overall benefits and costs associated with the changes?
If so, please briefly *describe* the study.
Please also provide the *contact information (Name and Title, Phone and Email)* of the relevant person(s) we should contact to access the study (if it is accessible).

B. Background Data

B-1) What traffic data (such as volume and composition, speeds, number of accidents and accident rates) does your Department collect and maintain on a regular basis?

Please provide the *contact information (Name and Title, Phone and Email)* of the relevant person(s) we should contact to access the data (if it is accessible).

B-2) Does your Department operate any instrumented highways (roadway facilities with a high density of traffic sensors and detectors collecting and recording data at short time intervals on an ongoing basis)?

If so, please describe the highways' location and characteristics, the date the system was implemented, and the main features (e.g., type and size) of the traffic data collection system (e.g., double- or single-loop detectors).

Please also provide the *contact information (Name and Title, Phone and Email)* of the relevant person(s) we should contact to access the data (if it is accessible) from these facilities.

C. Speed Limit Enforcement Decisions

C-1) What role, if any, does your State DOT play in determining the levels and location of highway patrol deployments for speed limit enforcement on high-speed roads?

C-2) If the Department is involved in such decisions, how does it decide where and how intensively speed limits should be enforced?

C-3) Were there changes in your State's enforcement policy following the repeal of the National Maximum Speed Limit in 1995?

If so, please describe them.

C-4) What are the levels of traffic fine for different degrees of speeding? Are there other penalties as well (e.g. driver's license revocation)?

C-5) What is the legal Blood Alcohol Content (BAC) in your State, and how and when has it changed in the last decade?

C-6) Does your State have graduated driver's licenses and if so, how and when did these arise? What sorts of restrictions on young drivers are in place?

C-7) Please suggest someone we might contact in another State agency (Department of Public Safety, State Police, etc.) for further information on speed limit enforcement decisions.

D. Speed Limit Change Decisions

D-1) Please describe how speed limits are determined for high-speed roadways in your State. In determining speed limits, how much importance is given to design speeds versus observed uncongested operating speeds?

Have any datasets been generated that compare speed limits, design speeds and operating speeds in your State? If so, please provide the *contact information (Name and Title, Phone and Email)* of the relevant person(s) we should contact to access these datasets (if it is accessible).

D-2) Please describe in detail the process by which your Department decides to modify (raise or lower) the posted speed limit on high-speed roads, either for individual road sections or for an entire class of facility (e.g. rural or urban interstates, other limited access facilities, other high-speed roadway).

D-3) Has the Department established any written rules or guidelines to be followed when making these decisions?

If so, please identify and describe them.

D-4) Please describe other factors (legal limitations, public opinion, interest groups, political considerations, etc.) that play a role in making decisions about raising speed limits.

D-5) Please provide the *contact information (Name and Title, Phone and Email)* of the relevant person(s) we should contact for further information about the speed limit change decisions.

E. General Comments

E-1) We welcome any observations that you may have about the impacts of speed limit changes on high-speed roads in your State. As an example, you might have comments on the following questions:

1. Overall, has the repeal of the NMSL affected traffic safety in your State?
2. Have speed limit changes on high-speed roads influenced driver behavior and/or traffic safety on other road classes as well?
3. Have truck route choices changed since the NMSL repeal? Are some portions of your State's roadway network either safer or less safe because of this?
4. Has the elimination of NMSL-related speed enforcement mandates changed the focus of highway patrol activities? Has this had an effect on traffic safety?
5. Have changes in speed limits on high-speed roads impacted the environment? the business community? public opinion? other impacts?
6. Any other issues that you would like to raise?

We will value any and all insights that you share with us, and we promise that no identifying information will be included in our summaries of this question's results.

Thank you for taking your valuable time to complete the survey

B Model of Attitudes Towards Speed Limit Level

As mentioned in Section 4.2.1, the 2000 Motor Vehicle Occupant Safety Survey (MVOSS) asked respondents if they thought that current speed limits were too low, about right, or too high. 76.6% of the respondents were satisfied with current speed limits, 16.2 % felt they were too low, and 7.2% thought they were too high. In comparison, Haglund and Aberg (2000) reported corresponding attitudes at 61.1%, 37.0%, and 1.9% by Swedish drivers on highways with a 90 kph (56 mi/h) speed limit. Of course, U.S. freeway speeds are often above 100 km/h, so Americans could be expected to be less likely to want higher limits than their Swedish counterparts.

In order to explore more deeply the determinants of drivers' attitudes towards speed limit levels, an ordered probit model of opinion about speed limits as a function of driver characteristics was developed. Data available from the MVOSS are described in Table 4-1, and the model coefficient estimates are presented in Table B-1.

Table B-1 reveals that male, employed, married, and higher-income drivers favor higher speed limits, in contrast to drivers of vans, SUVs, and pickup trucks. People who favor seat belt laws and those who experienced crashes (as drivers) in the past support lowering speed limits, while those who frequently pass others, recently experienced being stopped by a police officer, drink more often, and/or indicated a higher highway driving speed tend to favor speed limit increases.

Table B-1 – Results of Ordered Probit Model of Speed Limit Opinion

Variables	Initial Model			Final Model		
	Coeff.	Std.Err.	P-value	Coeff.	Std.Err.	P-value
Constant	0.7972	0.1865	0.0000	1.2464	0.1826	0.0000
Indicator for Male	-0.0327	0.0327	0.3174	-0.1959	0.0323	0.0000
Age	9.770E-03	5.308E-03	0.0657	0.0338	5.484E-03	0.0000
Age Squared	-7.620E-05	5.316E-05	0.1518	-2.022E-04	5.653E-05	0.0003
Hispanic	0.0197	0.0505	0.6965			
Married	4.838E-03	0.0365	0.8945	-0.0743	0.0385	0.0538
College Educated	1.988E-04	0.0291	0.9946			
Employed	-0.0215	0.0323	0.5054	-0.1124	0.0340	0.0010
Income	8.784E-07	1.707E-06	0.6068	-1.635E-06	4.488E-07	0.0003
Income Squared	-8.707E-12	1.133E-11	0.4423			
Indicator for Central City	4.358E-04	0.0355	0.9902			
Indicator for Van	0.0537	0.0458	0.2407	0.2785	0.0470	0.0000
Indicator for Pickup	0.0393	0.0441	0.3726	0.0962	0.0421	0.0225
Indicator for SUV	0.0583	0.0485	0.2296	0.1920	0.0488	0.0001
Indicator for Heavy Truck	-0.0644	0.0978	0.5101			
Indicator for Other Vehicle	-0.1071	0.2413	0.6573	-0.5126	0.2027	0.0114
Driving Frequency	3.074E-03	0.0300	0.9184			
Seatbelt Frequency	-0.0282	0.0212	0.1826	-0.0952	0.0206	0.0000
Seatbelt Law Support	0.0470	0.0196	0.0166	0.1291	0.0195	0.0000
Opinion of Other Drivers	0.0103	0.0164	0.5284			
Pressure to Exceed Speed Limit	-3.407E-03	0.0156	0.8276	0.0640	0.0158	0.0001
More Pass	0.0928	0.0428	0.0303	0.4841	0.0411	0.0000
Neither Pass	0.0923	0.1088	0.3963	0.2683	0.1023	0.0087
Pass Same	0.0715	0.0975	0.4634	0.1686	0.0940	0.0729

Speed on Highway	-3.861E-03	2.022E-03	0.0562	-0.0166	1.980E-03	0.0000
Stopped by Police	-0.0205	0.0573	0.7208	-0.0915	0.0395	0.0205
Recent Traffic Ticket	-0.0139	0.0716	0.8460			
Drinking Days	-2.249E-03	2.389E-03	0.3465	-7.867E-03	0.0021	0.0002
Number of Drinks	1.502E-04	9.553E-03	0.9875			
Drinking and Driving Days	-1.431E-03	7.327E-03	0.8452			
Injured in Crash	-0.0754	0.0816	0.3553	-0.3216	0.0670	0.0000
Injured as Driver	0.0396	0.0764	0.6044	0.1832	0.0703	0.0092
Number of Injury Events	-6.926E-04	0.0286	0.9807			
τ_0	N/A			N/A		
τ_1	2.4496	0.0398	0.0000	2.7755	0.0418	0.0000
Nobs.	4,136			4,136		
Loglik constants only	-2845.62			-2845.62		
Loglik	-2512.33			-2514.73		
LRI	0.1171			0.1163		
Adj. LRI	0.1055			0.1086		

Note: Y = 0 (current speed limits are too low), 1 (limits are about right) and 2 (limits are too high).

Figure B-1 illustrates some predicted responses to this question for different respondent characteristics. Older persons are predicted to respond that the current speed limits are too high; however, this trend is maximized at an age of about 80 years. The gender effect is much bigger than the vehicle-type effect: females are more likely to consider the current speed limits to be too high, regardless of the vehicle types that they use. Van drivers are estimated to be the most likely to favor lowering limits, followed by SUV drivers; pickup and passenger car drivers are the least likely to support lowering speed limits.

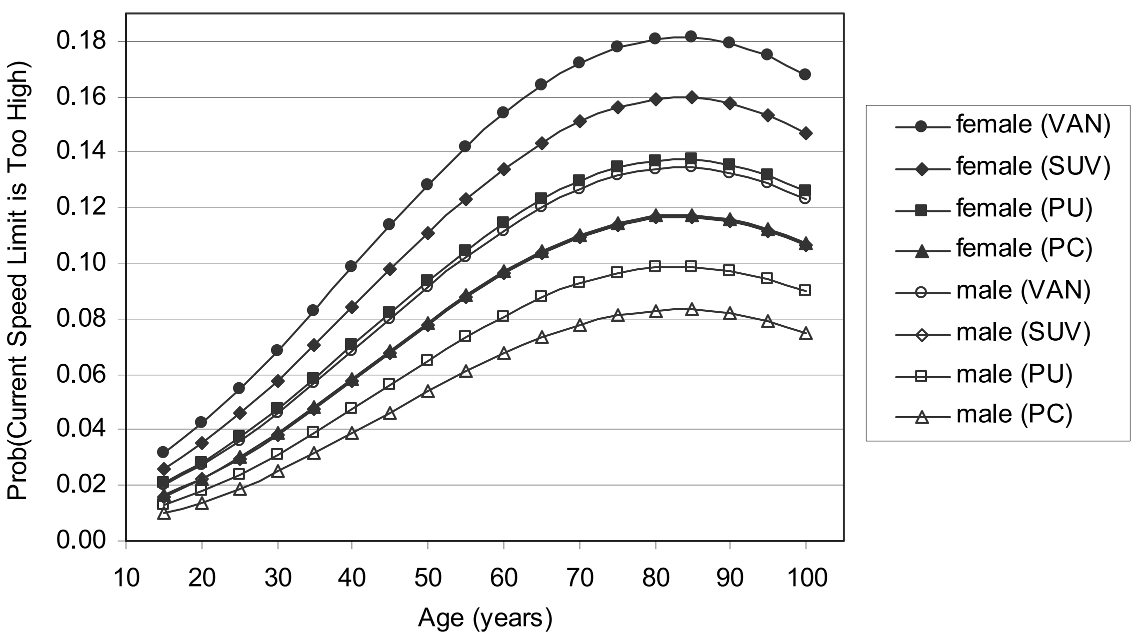

Figure B-1 – Probability of Responding that the Current Speed Limit Is Too High

Note: Reference individual is married and employed, and exhibits average values of all other explanatory variables included in the final model shown in Table B-1.

C Estimating Speed Variables from Orange County Traffic Detector Data

The traffic data used in the project's analyses of Orange County, California were collected from single-loop detectors. Such detectors can only measure the traffic count (the number of vehicles passing a loop detector in a sample cycle) and lane occupancy (the fraction of total time that a loop is "occupied" by vehicles) during a given time interval.

The following sections describe how average-speeds and speed variance were estimated from the 30-second count and occupancy measurements provided by Orange County's single-loop traffic detectors.

C.1 Estimation of Average Speed

The average speed of an individual vehicle is the distance it travels divided by its travel time. While activating a presence-type detector, a single vehicle travels a distance equal to the vehicle length (l_i) *plus* the detection zone length (l_d) during the detector's occupancy time (t_i). The speed can thus be estimated from the following formula (May, 1990):

$$v_i = \frac{3600}{5280}\left(\frac{l_i + l_d}{t_i}\right) \qquad \text{(C-1)}$$

where v_i = speed of individual vehicle (miles per hour), l_i = length of individual vehicle (feet), l_d = the loop detector size (feet), and t_i = individual vehicle occupancy time (seconds).

Thus, the *average* of several vehicles' speeds during a 30-second interval can be computed in miles per hour (mi/h) as follows:

$$\bar{v} = \frac{\sum v_i}{N} = \frac{3600}{5280}\left(\frac{\sum (l_i + l_d)/t_i}{N}\right) \approx \frac{3600}{5280} \times \frac{\sum (l_i + l_d)}{\sum t_i} \qquad \text{(C-2)}$$

The final part of this equation holds only if the speeds of all measured vehicles are equal during the 30-second interval.

Individual vehicle lengths are not available from single-loop detector data. Thus, in practice a single value of average vehicle length is assumed when making speed estimates, resulting in Equation C-3:

$$\hat{\bar{v}} = \frac{3600}{5280}\left(\frac{\bar{l}_v + l_d}{\bar{t}_o}\right) \qquad \text{(C-3)}$$

where $\bar{t}_o$ is average occupancy time per vehicle (or *%OCC* * 30 sec/*n*, where *%OCC* is the percentage of time the detector is occupied during the 30-sec interval and n is the number of vehicles detected in the same interval).

Equation C-3 can be modified to produce the following expression:

$$\hat{\bar{v}}_{l,t} = \frac{n_{l,t}}{30/3600}\left(\frac{100}{\%OCC_{l,t}}\right)\frac{\bar{l}_{l,t} + l_d}{5280} \tag{C-4}$$

where the subscripts *t* and *l* refer to the t^{th} 30-second interval and the l^{th} lane, respectively, and $\bar{l}_{l,t}$ represents average vehicle length during this same interval in the same lane.

Note that the effective vehicle length ($\bar{l}_v + l_d$) is unknown and not easily estimated. Many researchers have addressed the problem of computing vehicle speeds using single-loop detector data (e.g., Pushkar *et al*. 1994; Wang and Nihan 2000; Coifman *et al*. 2001; Coifman 2001; and Hellinga 2002).

A number of Caltrans employees in Orange County and at Division offices were contacted in an attempt to determine a robust estimate of effective lengths for the detector sites in the project's dataset. After several weeks of work using detection zone- and vehicle-length assumptions of 10 and 14.75 feet, respectively, it was decided to use the g-factors (the inverse of the effective lengths) from algorithms developed by the PeMS group at the University of California, Berkeley (Jia *et al*. 2001; PeMS 2002). These factors vary by station, lane, and every five-minute interval of every day of the week, and are automatically computed by the PeMS algorithm based on assumptions about free-flow speeds during uncongested periods (Chen *et al.* 2002).

Use of the PeMS g-factors in the project's speed calculations resulted in much more reasonable speed estimates than the original effective length assumption. However, it is not clear how accurate they are in any particular 30-sec interval, since they are intended to provide reasonable overall speed estimates, and suffer from a form of endogeneity bias.

C.2 Estimation of Speed Standard Deviation

C.2.1 Within Lanes

In order to infer speed variation from estimates of 30-sec speed averages (in other words, without data on individual vehicle speeds), it was necessary to assume that the distribution of speed choices underlying any 30-sec sample remains unchanged over several successive intervals; a period of 5 intervals (2.5 minutes) was chosen for this assumption. Within any interval, the average speed over five successive 30-second intervals ($\bar{\bar{v}}_{150\,\sec\, l,t}$) is used as a central point about which to evaluate the variation in individual 30-sec averages:

$$\bar{\bar{v}}_{150\sec l,t} = \frac{n_{l,t-2}\hat{\hat{v}}_{l,t-2} + n_{l,t-1}\hat{\hat{v}}_{l,t-1} + n_{l,t}\hat{\hat{v}}_{l,t} + n_{l,t+1}\hat{\hat{v}}_{l,t+1} + n_{l,t+2}\hat{\hat{v}}_{l,t+2}}{n_{l,t-2} + n_{l,t-1} + n_{l,t} + n_{l,t+1} + n_{l,t+2}} \quad \text{(C-5)}$$

$$SDL\hat{N}SPD_{l,t} = \sqrt{\sum_{s=t-2}^{t+2} n_{l,s}\left(\hat{\hat{v}}_{l,s} - \bar{\bar{v}}_{150\sec l,s}\right)^2 \Big/ \sum_{s=t-2}^{t+2} n_{l,s}} \quad \text{(C-6)}$$

where $n_{l,t}$ = traffic count in the t^{th} 30-second interval ($t = 1,2,\cdots$) for the l^{th} lane; $\hat{\hat{v}}_{l,t}$ = the average speed estimate in this same interval and lane; $SDL\hat{N}SPD_{l,t}$ = the estimate of standard deviation of individual vehicle speeds in this same interval and lane. Thus, data are recognized two intervals before and two intervals after each interval for which the estimators are coded.

C.2.2 Across Lanes

At a given station, several detectors simultaneously produce data for each of a group of adjacent lanes: in this situation, to compute an across-lane average there is no need to average over successive time intervals. Variations in average speeds across lanes during a single 30-second interval can be used to estimate between-lane speed variation. Taken together with within-lane variation (defined above), the total section speed variance can be determined. The formulae for across-lane average speed and speed standard deviation are as follows:

$$\bar{\bar{v}}_{accrosslanes,t} = \frac{\sum_l n_{l,t}\hat{\hat{v}}_{l,t}}{\sum_l n_{l,t}} \quad \text{(C-7)}$$

$$SD\hat{L}NS_t = \sqrt{\sum_l \left(\hat{\hat{v}}_{l,t} - \bar{\bar{v}}_{accrosslanes,t}\right)^2 \cdot n_{l,t} \Big/ \sum_l n_{l,t}} \quad \text{(C-8)}$$

where $n_{l,t}$ = traffic count for the t^{th} 30-second interval in the l^{th} lane; $\hat{\hat{v}}_{l,t}$ = the average speed in this same interval and lane; and $SD\hat{L}NS_t$ = the estimate of standard deviation in average speeds across lanes in this interval.

C.2.3 Within and Across Lanes

As noted, the total variation for a section consisting of multiple lanes can be estimated from its within-lane and across-lane (or between-lane, using more standard statistical terminology) variance estimates. The total is obtained from two sums of squares: the within- and between-lane sums of squares (*WSS* and *BSS,* respectively):

$$WSS_t = \sum_l n_{l,t} \cdot \left(\hat{\hat{v}}_{l,t} - \bar{\bar{v}}_{150\sec l,t}\right)^2 \quad \text{(C-9)}$$

$$BSS_t = \sum_l n_{l,t} \cdot \left(\hat{\hat{v}}_{l,t} - \bar{\bar{v}}_{accrosslanes,t}\right)^2 \quad \text{(C-10)}$$

$$TSS_t = WSS_t + BSS_t \tag{C-11}$$

$$SDS\hat{X}NSPD_t = \sqrt{\frac{TSS_t}{\sum_l n_{l,t}}} \tag{C-12}$$

where $SDS\hat{X}NSPD_t$ = the estimate of standard deviation in speeds of vehicles observed across all lanes in the section.

All these estimators are of some interest, but the speed standard deviations within each lane ($SDL\hat{N}SPD_{l,t}$) and across the entire roadway section ($SDSXNSPD_t$) are probably of greatest interest. Thus, model results for these variables have been emphasized in the discussion in the body of this report.

D Speed Choice in Northwest Washington State

The Washington Department of Transportation (WSDOT) Northwest (NW) regional office maintains traffic loop detector data for the northwest region of Washington State. Available data include traffic counts, occupancies and speeds by lane,[41] accumulated and output at 20-second intervals. However, the speed data are aggregated to 5-minute intervals for archiving and, unfortunately, the original 20-second data cannot be recovered.

HSIS data were matched to the speed detector site data based on route and milepost location information common to both datasets. The resulting dataset contained roadway design variables, road classification and location indicators, year indicators, and speed limits. Only 36 of the 122 traffic detector sites contained a reasonable number of *valid* speed records for the entire data period (1993-1996) and could be mapped to distinct road segments in the HSIS dataset. (Among these 36 sites, 21 are located on straight roadway segments.) This number of matches was far less than expected, and was a key reason why the models developed from these data did not provide reasonable estimates of average speed (and speed variance) at other sites in the Washington State network.

D.1 Data Preparation

The project contacted Matthew Bealieu in the Freeway Operations group of that office, and Mr. Bealieu put us in communication with Christian Cheney to obtain the actual data. The project received all traffic detector data for the region from 1988 through March 2003 on 32 CD-ROMs. These 25 years of traffic data can be mapped to any available crash, design or other type of data for which linear referencing (i.e. route and milepost) location information is available.

According to the User's Guide for these detector data (Ishimaru, 1998), the algorithm that was applied before July 1996 to estimate 5-minute average speed was in error: 20-second intervals with zero traffic volume were included in this computation as if their average speed were 0 mi/h. This results in an underestimation of average speeds, particularly during low-volume periods (e.g. late at night). Starting in July 1996, the zero-volume intervals are no longer included in the average speed calculation, and a proper weighted average is used.[42] Fortunately, the 20-sec vehicle counts are available for all periods, so a certain correction can be made to the pre-July 1996 average speed estimates. This correction involves inflating the speed estimates by 15 (the number of 20-sec intervals in a 5-minute period) and dividing the result by the number of 20-sec intervals in which vehicles were actually counted. This is not a true weighted average, as are the post-July 1996 averages, but it is nonetheless superior to the average speed estimates in the archived pre-July 1996 records.

Monthly speed variables were constructed from the processed 5-minute detector data. The variables included speed averages and variances for each month at each site. Note that, it is not possible in general to compute true vehicle speed variances without individual vehicle speed

[41] These sites use double-loop detectors, which are able to determine instantaneous vehicle speeds based on the time interval between activations of the individual loops in a pair and the (known) distance between the loops.
[42] The weighting factor is the count of vehicles in each of the 20-second sub-intervals.

data. However, the project developed a method to estimate approximate speed variances from the available WSDOT detector data by expanding the count-weighted variance of speed averages. This method relies on the identity $n\mathrm{V}(X_{avg}) = \mathrm{V}(X)$ if the X_i's are identically and independently distributed during the time periods of interest. Of course, it is unlikely that the speed distribution remains unchanged over the duration of a day, particularly on roadways that congest during certain periods. Thus, the method was applied separately to four distinct periods (AM peak, AM off-peak, PM peak, and PM off-peak) during the day.
First, segment averages for 5-minute intervals across lanes were computed. Segment daily averages were then obtained based on the segment 5-minute averages as follows:

$$AverageSpeed_{is} = \frac{\sum_{l} AverageSpeed_{il} \times Volume_{il}}{\sum_{l} Volume_{il}}$$

$$AverageSpeed_{ds} = \frac{\sum_{i=1}^{288} AverageSpeed_{si} \times Volume_{si}}{\sum_{i=1}^{288} Volume_{si}}$$

$$SpeedVariance_{ds} = \frac{\sum_{i=1}^{288} (AverageSpeed_{si} - AverageSpeed_{ds})^2 \times Volume_{si}}{\sum_{i=1}^{288} Volume_{si}}$$

where i indexes each of the 288 five-minute intervals in a day, l indexes each lane in a segment s, and d indexes the day.

Next, average speed and speed variance were calculated for specific time periods in a day using the 5-minute statistics for an entire month:

Daily AM peak: 7:30-8:30am (i = 90 through 102)

$$SpeedAMPK_{ds} = \frac{\sum_{i=90}^{102} AverageSpeed_{si} \times Volume_{si}}{\sum_{i=90}^{102} Volume_{si}}$$

$$VarianceAMPK_{ds} = \frac{\sum_{i=90}^{102} (AverageSpeed_{si} - AverageSpeed_{ds})^2 \times Volume_{si}}{\sum_{k=90}^{102} Volume_{jk}}$$

Daily AM off peak: 10:00-noon (i = 120 through 144)

$$SpeedAMOP_{ds} = \frac{\sum_{i=120}^{144} AverageSpeed_{si} \times Volume_{si}}{\sum_{i=120}^{144} Volume_{si}}$$

$$VarianceAMOP_{ds} = \frac{\sum_{i=120}^{144} \left(AverageSpeed_{si} - AverageSpeed_{ds}\right)^2 \times Volume_{si}}{\sum_{i=120}^{144} Volume_{si}}$$

Daily PM peak: 4:00-6:00pm (i = 192 through 216)

$$SpeedPMPK_{ds} = \frac{\sum_{i=192}^{216} AverageSpeed_{si} \times Volume_{si}}{\sum_{i=192}^{216} Volume_{si}}$$

$$VariancePMPK_{ds} = \frac{\sum_{i=192}^{216} \left(AverageSpeed_{si} - AverageSpeed_{ds}\right)^2 \times Volume_{si}}{\sum_{i=192}^{216} Volume_{si}}$$

Daily PM off peak: 9:00-11:00pm (i = 252 through 276)

$$SpeedPMOP_{ds} = \frac{\sum_{i=252}^{276} AverageSpeed_{si} \times Volume_{si}}{\sum_{i=252}^{276} Volume_{si}}$$

$$VariancePMOP_{ds} = \frac{\sum_{i=252}^{276} \left(AverageSpeed_{si} - AverageSpeed_{ds}\right)^2 \times Volume_{si}}{\sum_{i=252}^{276} Volume_{si}}$$

Based on the results from the above equations, average monthly speeds and speed variances for each month *m* were computed as follows:

Monthly Overall

$$SpeedMonthly_{ms} = \frac{\sum_{d=1}^{31} AverageSpeed_{sd} \times Volume_{sd}}{\sum_{d=1}^{31} Volume_{sd}}$$

$$VarianceMonthly_{ms} = \frac{\sum_{d=1}^{31} VarianceSpeed_{sd} \times Volume_{sd}}{\sum_{d=1}^{31} Volume_{sd}}$$

Monthly AM peak: 7:30AM–8:30AM

$$SpeedAMPK_{ms} = \frac{\sum_{d=1}^{31} SpeedAMPK_{sd} \times VolumeAMPK_{sd}}{\sum_{d=1}^{31} VolumeAMPK_{sd}}$$

$$VarianceAMPK_{ms} = \frac{\sum_{d=1}^{31} VarianceAMPK_{sd} \times VolumeAMPK_{sd}}{\sum_{d=1}^{31} VolumeAMPK_{sd}}$$

Monthly AM off-peak: 10:00AM–noon

$$SpeedAMOP_{ms} = \frac{\sum_{d=1}^{31} SpeedAMOP_{sd} \times VolumeAMOP_{sd}}{\sum_{d=1}^{31} VolumeAMOP_{sd}}$$

$$VarianceAMOP_{ms} = \frac{\sum_{d=1}^{31} VarinaceAMOP_{sd} \times VolumeAMOP_{sd}}{\sum_{d=1}^{31} VolumeAMOP_{sd}}$$

Monthly PM peak: 4:00PM–6:00PM

$$SpeedPMPK_{ms} = \frac{\sum_{d=1}^{31} SpeedPMPK_{sd} \times VolumePMPK_{sd}}{\sum_{d=1}^{31} VolumePMPK_{sd}}$$

$$VariancePMPK_{ms} = \frac{\sum_{d=1}^{31} VariancePMPK_{sd} \times VolumePMPK_{sd}}{\sum_{d=1}^{31} VolumePMPK_{sd}}$$

Monthly PM off-peak: 9:00PM–11:00PM

$$SpeedPMOP_{ms} = \frac{\sum_{d=1}^{31} SpeedPMOP_{sd} \times VolumePMOP_{sd}}{\sum_{d=1}^{31} VolumePMOP_{sd}}$$

$$VariancePMOP_{ms} = \frac{\sum_{d=1}^{31} VariancePMOP_{sd} \times VolumePMOP_{sd}}{\sum_{d=1}^{31} VolumePMOP_{sd}}$$

In all of the above equations, m indexes the month, d indexes the day, s indexes the segment, and i indexes the sequential number of the 5-minute intervals (from 1 to 288, since there are 288 5-minute intervals in a day, where for example i =1 indicates the interval from 00:00AM–00:05AM). $SpeedMonthly$ and $VarianceMonthly$ denote average monthly speed and speed variance. $SpeedAMPK$, $VarianceAMPK$, $SpeedAMOP$, $VarianceAMOP$, $SpeedPMPK$, $VariancePMPK$, $SpeedPMOP$, $VariancePMOP$ denote monthly average speeds and variances for the AM/PM peak (PK) or off-peak (OP) periods. Finally, *Volume* denotes a traffic volume for the indexed time period (e.g., *VolumeAMPK* is a traffic volume during an AM peak period).

Table D-1 presents summary statistics for the variables in the dataset.

Table D-1 – Speed Choice Data Summary Statistics for 36 Detector Sites

Variable	*Average*	*Std. Dev.*	*Min*	*Max*
AverageSpeedMonthly	49.05	10.19	20.2	76.8
VarianceSpeedMonthly	91.34	79.62	5.18	441.2
AverageSpeedAMPeak	46.68	13.79	6.80	75.5
VarianceSpeedAMPeak	29.82	38.49	0.50	470.6
AverageSpeedAMOffPeak	49.78	12.38	13.5	78.2
VarianceSpeedAMOffPeak	23.66	59.15	0.80	1161.3
AverageSpeedPMPeak	48.47	11.05	16.9	76.3
VarianceSpeedPMPeak	43.47	43.69	1.27	243.3
AverageSpeedPMOffPeak	47.37	12.41	14.1	77.7
VarianceSpeedPMOffPeak	21.57	36.39	0.56	608.2
Segleng	0.117	0.103	0.02	0.53
Curvleng	519.2	706.1	0.0	2640.0
Degcurve	0.65	0.94	0.0	3.17
Vertical curve grade	0.57	2.70	-4.84	4.0
Vertical curve length	616.1	548.2	0.0	1800.0
Median width	37.65	24.13	7.00	155.0
Shoulder width	17.15	6.60	0.00	24.00
Number of lanes	6.332	0.902	4	8
Speed limit	59.18	1.86	55	60
Indicator for 50k <= population < 100k	0.748	0.434	0	1
Indicator for 100k <= population < 250k	0.563	0.497	0	1
AADT	139,955	51,353	34,552	241,255
Indicator for year 1993	0.046	0.209	0	1
Indicator for year 1994	0.119	0.324	0	1
Indicator for year 1995	0.265	0.442	0	1
Indicator for year 1996	0.570	0.496	0	1

Note: All sites are located on urban interstate highways in rolling terrain.

D.2 Model Estimation and Analysis

Models of average speed and speed variance were specified and estimated using these monthly speed measures as well as HSIS speed limit and roadway design variables. Five separate models were developed, corresponding to an entire day and to individual time periods within a day, for average speed and for speed variance.

In order to guarantee positive predictions, a log-linear specification was used in these speed choice models. To account for possible heteroscedasticity, White's consistent estimator (White 1980) was used to estimate standard errors of the model parameter estimates. The models were developed in a stepwise fashion, beginning with an inclusive specification that incorporated all variables in Table D-1, and deleting one by one those variables that were found to be not statistically significant at the 0.05 level.

Of the ten estimated models, the two PM peak period models (Eqs. 1 and 2) were selected as being representative of the results obtained. More specifically, the models were selected due to: (1) the intuitive sign of the speed limit variable's coefficient estimate (i.e., positive) in the average speed model; (2) the statistical significance of the speed limit coefficients; and (3) the higher goodness of model fit (R-squared values of 0.484 and 0.265, respectively). The models are as follows:

$$AverageSpeedPMPeak = \exp\left\{\begin{array}{l} 0.3822 + 0.0608 \times \text{Speed limit} + 0.000138 \times \text{Horizontal curve length} \\ - 0.1747 \times \text{Degree of curve} - 0.0286 \times \text{Vertical grade} \\ + 0.0000342 \times \text{Vertical curve length} + 0.0223 \times \text{Shoulder width} \\ - 0.0385 \times \text{Number of lanes} - 0.0000196 \times \text{AADT per lane} \\ - 0.0783 \times \text{Indicator for } 50\text{k} \le \text{population} < 100\text{k} \\ + 0.3534 \times \text{Indicator for } 100\text{k} \le \text{population} < 250\text{k} \\ + 0.2816 \times \text{Indicator for year 1994} + 0.0451 \times \text{Indicator for year 1996} \end{array}\right\} \quad \text{(D-1)}$$

(R-sqrd.=0.484, Nobs. = 437, and all p-values are less than 0.05)

$$VarianceSpeedPMPeak = \exp\left\{\begin{array}{l} - 0.4314 + 0.0896 \times \text{Speed limit} + 0.1177 \times \text{Degree of curve} \\ - 0.0743 \times \text{Vertical grade} - 0.00632 \times \text{Median width} \\ + 0.0428 \times \text{Shoulder width} - 0.4153 \times \text{Number of lanes} \\ + 0.3986 \times \text{Indicator for } 50\text{k} \le \text{population} < 100\text{k} \\ + 0.6076 \times \text{Indicator for } 100\text{k} \le \text{population} < 250\text{k} \\ - 0.2613 \times \text{Indicator for year 1996} \end{array}\right\} \quad \text{(D-2)}$$

(R-sqrd.=0.265, Nobs. = 437, and all p-values are less than 0.05)

These equations predict quite large effects of speed limit changes on speed average and variance. For example, a 5 mi/h speed limit increase is predicted to increase average PM peak speed by 35%. For any realistic highway situation, this percentage increase translates into an absolute increase in average driving speed that is greater than the speed limit increase itself. This is in contrast to a number of studies that have found that, following a speed limit change, the average speed changes by less than the speed limit change (e.g., Ossiander and Cummings 2002; Jernigan and Lynn 1991; Upchurch 1989).

A number of factors may have contributed to these model results. To some extent, they may have occurred because speed limits proxy for a great many safety features that are unobserved in the data and thus are uncontrolled for in the models. For example, while speed limits tend to increase with horizontal curve radius and shoulder width, which are included in the models, they also tend to go up with sight distance, clear zone width, and pavement condition – all variables that are unobserved. As a result, the speed limit coefficient is likely to be biased upwards.

An additional factor may be the small size of the available dataset: only 36 sites offered complete data for this analysis. Finally, rather heroic assumptions had to be made in developing average speed estimates before 1996, as well as for all the speed variance estimates.

In order to address these issues, supplementary datasets were sought for analysis. To this end, 16 sites in Austin, Texas and four sites in Washington State (two rural and two urban; two that experienced speed limit changes and two that did not) were examined. The first offered data on individual vehicle speeds for an hour at each site and the second more aggregate traffic data over several years. These datasets and their analyses are discussed in sections 4.2.3 and 4.2.4.

E Synthetic Speed Choice Model Data

Section 4.2.5 discussed the development and analysis of a rational speed choice model based on the hypothesis that a driver chooses the speed that minimizes the generalized cost of travel, which includes the time cost, expected crash cost and expected legal cost components associated with driving at a particular speed. It was not possible to solve analytically the minimization problem resulting from this formulation, so a numerical approach was adopted.

Two synthetic datasets were generated, in which each record consisted of specific values for each of the parameters and variables used in the model. For each record (i.e. each set of generated parameter and variable values), the optimum speed was then determined using the MATLAB software package (Mathworks Inc., 1992) and inserted in the corresponding dataset record. A regression analysis was then performed using these datasets to relate the optimum speed to the key explanatory variables.

This appendix describes the generation of the two synthetic datasets used in the analysis of the rational speed choice model.

E.1 Dataset 1

495,000 (= 10*10*10*9*11*5) data points were generated using assumed values for parameters and variables shown in Tables E-1 and E-2. Table E-3 presents descriptive statistics of the generated dataset.

Table E-1 – Parameter Values Assumed for Generation of Dataset 1

Coefficients	Assumed values	Number of values
b_0^t	0.01	1
b_1^t	0.01+0.005*N(0,1)	10
b_0^c	0.00033	1
b_1^c	0.000001	1
b_2^c	0.00000075+0.000000375*N(0,1)	10
a_0^c	500	1
a_1^c	5	1
b_0^l	0.0024	1
b_1^l	0.000001	1
b_2^l	0.000015+0.0000075*N(0,1)	10
a_0^c	10	1
a_1^c	8	1

Table E-2 –Variable Values Assumed for Generation of Dataset 1

Variables	Assumed values	Number of values
WAGE ($/veh-h)	10 to 50 by increment 5	9
SSPD (mi/h)	70 to 120 by increment 5	11
SL (mi/h)	55 to 75 by increment 75	5

Table E-3 – Descriptive Statistics for Dataset 1

Variables	N	Minimum	Maximum	Mean	Std. Dev.
SPEED (mi/h)	495,000	59.1	100.3	78.1	9.5
WAGE ($/veh-h)	495,000	10.0	50.0	30.0	12.9
SSPD (mi/h)	495,000	70.0	120.0	95.0	15.8
SL (mi/h)	495,000	55.0	75.0	64.9	7.0

E.2 Dataset 2

1,856,250 (= 5*5*3*5*5*3*6*11*5) speed data points were generated using assumed values for parameters and variables shown in Tables E-4 and E-5. Table E-6 presents descriptive statistics of the generated dataset.

Table E-4 – Parameter Values Assumed for Generation of Dataset 2

Coefficients	Assumed values	Number of values
b_0^t	0.01	1
b_1^t	$0.01+\sqrt{0.0013}*N(0,1)$	5
b_0^c	0.00033	1
b_1^c	0.000001	1
b_2^c	$0.00000075+\sqrt{0.000000000001}*N(0,1)$	5
a_0^c	500	1
a_1^c	$5+1*N(0,1)$	3
b_0^l	0.0024	1
b_1^l	$0.000001+\sqrt{0.0000000000001}*N(0,1)$	5
b_2^l	$0.000015+\sqrt{0.000000000025}*N(0,1)$	5
a_0^c	10	1
a_1^c	$8+\sqrt{2}*N(0,1)$	3

Note: The variances for generation were set for each coefficient not to change its sign.

Table E-5 –Variable Values Assumed for Generation of Dataset 2

Variables	Assumed values	Number of values
WAGE ($/veh-h)	10 to 50 by increment 7	6
SSPD (mi/h)	70 to 120 by increment 5	11
SL (mi/h)	55 to 75 by increment 5	5

Table E-6 – Descriptive Statistics for Dataset 2

Variables	N	Minimum	Maximum	Mean	Std. Dev.
SPEED (mi/h)	1,856,250	59.3	104	80.0	10.3
WAGE ($/veh-h)	1,856,250	10	45	27.5	12.0
SSPD (mi/h)	1,856,250	70	120	95.0	15.8
SL (mi/h)	1,856,250	55	75	64.9	7.0

F Crash Occurrence Models Using Unclustered HSIS Data

The project originally attempted to develop models of crash occurrence that were spatially highly disaggregate, using data for years 1993 through 1996 and 1999 through 2002 from the HSIS records for Washington State. The eight years of data come from roadway segments along seven interstates and 143 state highways.

The intended approach was to develop models of crash count by crash or injury severity, based on speed estimates from the models of Chapter 4, as well as on roadway design and use information. Since the individual roadway segments in the HSIS database are very short, the vast majority of segment crash counts were zero.

Using this dataset of disaggregate crash observations, eight different models were evaluated for crash counts; these included standard Poisson (PO) and negative binomial (NB) models, zero-inflated Poisson (ZIP) and negative binomial (ZINB) models, and fixed and random effects Poisson (FEPO/REPO) and negative binomial (FENB/RENB) models. Recognizing that crash counts do not equal crash victim counts, six different count variables were used as dependent variables: the numbers of fatalities, injuries, fatal crashes, injury crashes, property damage only (PDO) crashes, and total crashes. A total of 48 model formulations were explicitly evaluated, resulting from 6 dependent variables × 8 count models.

Statistical tests were performed in order to select a final model for each of the six crash counts modeled here. The random effects negative binomial (RENB) model performed best for all six crash responses, suggesting that intra-segment heterogeneity over time as well as inter-segment heterogeneity across segments contribute to over-dispersion in all crash and victim counts, and that unobserved factors affecting crash occurrence tend to be distributed randomly across roadway segments.

However, none of the final models could be considered satisfactory. They all presented problems in terms of model specification validity,[43] intuitiveness, and comparison issues. (For example, Hausman's test turned out to be inapplicable for this modeling situation.) The project therefore abandoned this disaggregate modeling approach and decided to work with aggregate forms of the dataset, obtained through clustering methods, as discussed in the body of the report.

This appendix describes the data that were used and the analyses that were conducted in this investigation.

F.1 Data Preparation

The crash occurrence model described here was developed using the 1993-1996 and 1999-2002 HSIS data for Washington State. New, shorter segments were created in order to provide an 8-year panel dataset for these segments. Only mainline segments were chosen, resulting in 100,457 segments for each of the 8 years. The AADT values for years 1999 through 2001 were missing and had to be linearly interpolated using the AADT in years 1993 through 1996 and in

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[43] This was especially true of the fatal crash count models.

2002. This interpolation worked reasonably well: for the 100,457 segments, the R squared value was 0.60.

After deleting observations with missing or abnormal values for the required variables (e.g., AADTs per lane equal to 0 or over 24,000 vehicles, and degrees of curvature higher than 29 degrees per 100 ft of centerline, 953,820 observations remained.

Some segments experienced significant changes in their design attributes between 1996 and 2002. The attributes considered here are horizontal curve length, curve degree, access control class, functional class, median width, terrain, region, right shoulder width and vertical grade. Since geometric records for years 1999 through 2001 are unavailable, segments exhibiting differences greater than 5% in one of these key geometric features were deleted, leaving 753,260 valid observations.

From these, only segments longer than 0.05 mile were chosen for analysis, in order to provide a reasonable length of unchanging design conditions. This selection may cause some sample bias, but it also reduces noise from an overabundance of zero-crash count records. Segments with a speed limit lower than 50 mi/h were also eliminated.

After all these manipulations, there remained an unbalanced panel dataset consisting of 277,020 observations covering 41,434 segments. Descriptive statistics for the resulting dataset are shown in Table F-1.

F.2 Model Estimation and Analysis

Panel data crash occurrence models were estimated using the HSIS dataset mentioned above. Random effects, fixed effects and zero-inflated negative binomial models (RENB, FENB and ZINB) were all calibrated.

The model estimation results were subjected to a series of statistical tests including likelihood ratio (LR) tests, Vuong and Hausman tests, and comparisons of the Aikaike and Bayesian Information Criteria (AIC and BIC) values (Kweon and Kockelman 2003b). Furthermore, the results were scrutinized with respect to the intuitiveness of the coefficient signs and their consistency across different models. Based on this review, the RENB model proved to be the single most effective model for estimating all crash counts.

The RENB model specification appears as a Poisson conditioned on a gamma, as follows:

$$\Pr\left(y_{it} \mid x_{it}, \delta_i\right) = \frac{e^{-\gamma_{it}} \gamma_{it}^{y_{it}}}{y_{it}!} \quad \text{where} \quad \gamma_{it} \mid \delta_i \sim Gamma\left(\lambda_{it}, \delta_i\right)$$

Here, y_{it} is the number of crashes or victims in year *t* along segment *i*, x_{it} is the set of explanatory variables (including speed limits and design variables), $\lambda_{it} = \exp\left(x_{it}'\beta\right)$ and δ_i is a dispersion parameter (random effect) specific to each road segment *i* (StataCorp, 2003). The

RENB model allows the dispersion parameter to vary such that $1/(1+\delta_{it}) \sim beta(p,q)$ (based on a standard beta, with limiting values of 0 and 1). This approach yields the following joint probability over all time periods $(1,2,\ldots,T_i)$ for each segment *i*:

$$\Pr\left(y_{i1},K,y_{iT_i} \mid X_i\right) = \frac{\Gamma(p+q)\Gamma\left(p+\sum_t \lambda_{it}\right)\Gamma\left(q+\sum_t y_{it}\right)}{\Gamma(p)\Gamma(q)\Gamma\left(p+q+\sum_t \lambda_{it}+\sum_t y_{it}\right)} \prod_t \frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)}$$

Several rate specifications were explored, with explanatory variables included either linearly or logarithmically within the exponential function. Those included logarithmically have a multiplicative effect, as illustrated for *VMT* in the following equation:

$$\lambda(x,VMT) = VMT^{\alpha}\exp(\beta x) = \exp\left(\beta x + \alpha\ln(VMT)\right).$$

In this study, α is restricted to equal 1.0, thus implying a constant crash rate. Since the models control for congestion levels, via an AADT/lane variable, it is not felt necessary to allow the crash rate to vary with VMT.

Final estimation results for the RENB models are shown in Table F-2, and the expected percentage changes in crash rates corresponding to changes in all variables are provided in Table F-3. It should be noted that due to the exponential transformation (which ensures crash rate non-negativity), the effects of the model coefficients are not as obvious as those of an ordinary linear model. For such models, an incidence rate ratio (IRR) is used to describe marginal effects (Long, 1997):

$$IRR(x_j) = \frac{\exp[\beta_1 x_1 + \ldots + \beta_j(x_j+1) + \ldots + \beta_J x_J]}{\exp[\beta_1 x_1 + \ldots + \beta_j x_j + \ldots + \beta_J x_J]} = \exp(\beta_j)$$

Thus, if β_j = -0.1, the associated IRR(x_j) = exp(-0.1) = 0.905, so a unit increase in x_j is estimated to reduce the mean crash rate by 9.5%, assuming all other factors remain constant. This ratio is used in the calculation of the results presented in Table F-3.

To test the reasonableness of these RENB model predictions, actual crash counts and rates were compared to predicted values. For each observation in the dataset, the predicted or expected crash count can be expressed as the following:

$$E(y_{it} \mid x_{it}) = E(\gamma_{it}) = E_{\delta_i}\left(E(\gamma_{it} \mid \delta_i)\right)$$

Since $\gamma_{it} \mid \delta_i \sim Gamma(\lambda_{it}, \delta_i)$, this can be further calculated as follows:

$$E(y_{it} \mid x_{it}) = E_{\delta_i}(\lambda_{it}\delta_i) = \lambda_{it}E(\delta_i) = \exp(x_{it}'\beta) \times E(\delta_i)$$

Since $1/(1+\delta_{it}) \sim beta(p,q)$, $\delta_i \sim betai(p,q)$ where $betai(\cdot)$ stands for a beta-prime (inverted beta) distribution which has a mean $\frac{q}{p-1}$ (Borghers and Wessa, 2005). Therefore

$$E\left(y_{it} \mid x_{it}\right) = \exp\left(x_{it}'\beta\right) \times \frac{q}{p-1}$$

In this fashion, expectations of crash counts and crash rates were calculated and compared to the actual values, as shown in Table F-4. When summed over all time periods and segments, the model predictions are very close to the actual totals, differing by less than 1.4% in counts and 5.4% in rates.

Interestingly, the models' parameter estimates suggest that higher speed limits do not affect fatality counts or fatal crash counts in a statistically significant way, and that they may slightly reduce the rate of injuries and injury crashes. For PDO crash and total crash counts, the speed limit is estimated to relate to the lowest crash rates when it is between 55 and 60 mi/h, but the effect is practically negligible.

The insensitivity of fatal counts to speed limits is counterintuitive and may stem from several sources. Perhaps the two most striking[44] are: (1) a lack of variation in fatality counts, due to their relative rarity, and (2) a positive correlation between speed limits and unobserved safety features, such as sight distances and pavement quality (thus biasing the speed limit variable's coefficients towards zero). The second of these two issues may also be at play in biasing speed limit effects downward for other crash rate estimates. Without controlling for these confounding variables, it is difficult to obtain conclusive results regarding the true effect of speed limits.

One way to address this issue is to consider only those facilities whose speed limits changed during the study period, and to compare their respective before and after crash counts. Unfortunately, the dependent variable in the before and after method can be negative, while standard count data models only apply to non-negative numbers. It would also be improper to use conventional discrete choice models for the crash count analysis because those models consider the numbers to be the coding of different categories rather than an actual number of crashes.

In conclusion, the panel models for discrete counts used here offer valuable information on a host of design and use variables while suggesting that speed limits have little effect. The empirical predictions of significant effects (both statistically and practically) for a number of variables (including shoulder width, access control, terrain, and area type) are revealing. The lack of significance for speed limit effects is intriguing.

[44] Other potential reasons for this result are the lack of data for two key years (1997 and 1998), the inclusion of indicator variables to control for distinct years in the dataset (to reflect trends, which may coincide with speed limit adjustments), and the lack of a serial model for error terms (which may mimic the natural ordering of the data).

Table F-1 – Variable Definitions and Summary Statistics

Variables	Mean	Std. Dev.	Min	Max
Dependent Variables				
Number of fatalities	4.653E-03	7.813E-02	0	5
Number of injuries	0.2615	1.0794	0	49
Number of fatal crashes	4.076E-03	6.422E-02	0	2
Number of injury crashes	0.1646	0.6299	0	26
Number of PDO* crashes	0.2093	0.7541	0	42
Number of total crashes	0.3779	1.2340	0	58
Independent Variables				
Speed-Related Variables				
Speed limit (mi/h)	5.380E+01	8.4147	25	70
Speed limit squared (mi^2/hr^2)	2.965E+03	8.441E+02	625	4900
Indicator for differential auto-truck speed limits	0.4901	0.4999	0	1
Roadway Design Variables				
Segment length (mile)	0.1236	0.1161	0.05	2.42
Horizontal curve length (ft)	3.732E+02	8.481E+02	0	12683
Degree of curvature (°/100ft)	1.0020	2.3124	0	28.65
Vertical curve length (ft)	4.928E+02	5.850E+02	0	6700
Vertical grade (%)	1.6857	1.7604	0	10.85
Indicator for median existence	0.1745	0.3795	0	1
Shoulder width (ft)	3.5931	3.1163	0	25
Number of lanes	2.5072	1.0782	2	9
Roadway Classification & Location Variables				
Indicator for interstate highway	0.0325	0.1774	0	1
Indicator for limited access	0.2887	0.4532	0	1
Indicator for principal arterial	0.1055	0.3072	0	1
Indicator for rolling terrain	0.7344	0.4417	0	1
Indicator for mountainous terrain	0.0793	0.2702	0	1
Indicator for rural area	0.8817	0.3230	0	1
Indicator for population < 50k	0.0923	0.2894	0	1
Indicator for 50k⩽ population<100k	1.462E-02	0.1200	0	1
Indicator for 100k⩽ population<250k	8.166E-03	8.999E-02	0	1
Indicator for northwest region	0.1046	0.3060	0	1
Indicator for northeast region	0.3673	0.4821	0	1
Indicator for southwest region	0.1855	0.3887	0	1
Indicator for southeast region	0.1986	0.3990	0	1
Traffic Volume & Yearly Indicator Variables				
AADT per lane (veh/day/lane)	2.878E+03	3.540E+03	44	23893
Average daily VMT (veh-mile/day)	1.127E+03	2.610E+03	4.75	71776
Indicator for year 2002	0.1092	0.3119	0	1
Indicator for year 2001	0.1092	0.3119	0	1
Indicator for year 2000	0.1092	0.3119	0	1
Indicator for year 1999	0.1092	0.3118	0	1
Indicator for year 1996	0.1482	0.3553	0	1
Indicator for year 1995	0.1487	0.3557	0	1
Indicator for year 1994	0.1482	0.3553	0	1

Table F-2 – Final Model Results for Six Crash/Victim Counts (Random Effects Negative Binomial Models)

Dependent Variable	Fatality		Fatal Crash		Injury		Injury Crash		PDO Crash		Total Crash	
Independent Variable	Coef.	t-stat..	Coef.	t-stat..	Coef.	t-stat..	Coef.	t-stat..	Coef.	t-stat..	Coef.	t-stat..
Constant	-9.72	-52.83	-5.92	-6.66	-6.16	-45.83	-3.80	-22.91	-3.29	-20.19	-3.50	-25.01
Speed limit (mi/h)					-4.81E-02	-8.89	-4.77E-02	-8.04	-7.11E-02	-12.20	-5.52E-02	-10.80
Speed limit squared (mi^2/hr^2)					3.40E-04	6.10	3.33E-04	5.51	5.66E-04	9.33	4.34E-04	8.14
Indicator for differential auto-truck speed limits									-6.41E-02	-2.70	-3.86E-02	-2.05
Segment length (mile)					-5.06E-01	-9.80	-5.34E-01	-9.32	-5.63E-01	-10.74	-5.32E-01	-11.71
Horizontal curve length (ft)					-7.20E-05	-7.85	-7.59E-05	-7.44	-5.79E-05	-6.43	-6.09E-05	-7.97
Degree of curvature (°/100ft)	9.13E-02	6.97	9.10E-02	6.93	4.39E-02	11.33	4.34E-02	10.16	2.97E-02	7.51	4.13E-02	12.82
Vertical curve length (ft)					-6.88E-05	-5.42	-6.96E-05	-4.97	-5.72E-05	-4.50	-6.66E-05	-6.17
Vertical grade (%)					-6.14E-02	-1.76	-1.02E-01	-2.39	-1.12E-01	-2.89	-1.03E-01	-3.04
Indicator for median existence					2.00E-02	4.27	1.81E-02	3.51	2.66E-02	5.58	2.30E-02	5.78
Shoulder width (ft)					-6.27E-02	-15.31	-6.61E-02	-14.61	-6.74E-02	-16.05	-6.65E-02	-18.09
Number of lanes	-2.63E-01	-9.73	-2.62E-01	-9.67			3.73E-02	3.52	6.64E-02	7.10	4.46E-02	5.21
Indicator for interstate highway							-1.02E-01	-2.60	-1.01E-01	-2.92	-7.68E-02	-2.41
Indicator for limited access					-1.38E-01	-6.08	-1.57E-01	-6.27	-6.71E-02	-2.97	-9.77E-02	-5.15
Indicator for principal arterial					8.66E-02	3.75	1.43E-01	5.09			7.36E-02	3.13
Indicator for rolling terrain									6.06E-02	3.26		
Indicator for mountainous terrain					2.42E-01	7.20	2.21E-01	5.93	3.87E-01	10.58	2.46E-01	8.81
Indicator for rural area									-1.88E-01	-6.26	-1.01E-01	-3.85
Indicator for population < 50k	-3.69E-01	-3.50	-3.59E-01	-3.41	-1.01E-01	-4.77	-9.45E-02	-4.22	-8.51E-02	-2.96	-9.65E-02	-3.95
Indicator for northwest region	-3.40E-01	-3.25	-3.31E-01	-3.17	-2.00E-01	-7.84	-1.79E-01	-6.12			-8.03E-02	-3.86
Indicator for northeast region					-0.18	-7.59	-2.01E-01	-7.37	-7.66E-02	-3.47	-1.24E-01	-7.57
Indicator for southwest region					-0.26	-11.33	-2.83E-01	-10.62	-3.96E-02	-1.81	-1.30E-01	-7.38
Indicator for southeast region					-0.13	-4.75	-1.49E-01	-4.83	9.02E-02	3.60		
AADT per lane (veh/day/lane)	-6.84E-05	-8.01	-6.91E-05	-8.08	-1.28E-05	-5.31	-1.19E-05	-4.46	-1.49E-05	-6.23	-1.64E-05	-8.41
Indicator for year 2002									1.63E-01	6.44	1.08E-01	4.72
Indicator for year 2001									1.01E-01	3.96	7.96E-02	3.48
Indicator for year 2000					5.59E-02	3.03	5.32E-02	3.18	1.27E-01	5.01	1.09E-01	4.79
Indicator for year 1999					6.82E-02	3.67	7.60E-02	4.54	9.74E-02	3.77	1.02E-01	4.44
Indicator for year 1996					1.24E-01	7.52	1.07E-01	7.40	1.08E-01	4.40	1.27E-01	5.80
Indicator for year 1995					6.65E-02	3.99	4.54E-02	3.08			4.53E-02	3.15
Indicator for year 1994					3.06E-02	1.78					3.01E-02	2.14
Ln(p)	3.89	2.31	7.38	5.08	1.25	61.30	3.19	65.81	3.17	75.92	2.87	101.20
Ln(q)	2.60	1.39	2.17	1.39	1.05	36.70	0.39	17.93	0.53	26.14	0.63	37.89
LRI	0.037		0.040		0.018		0.018		0.018		0.015	

*The coefficient for ln(VMT) was constrained to equal 1.0. In other words, average daily VMT is modeled as an *exposure* variable.

Table F-3 – Expected Percentage Changes in Crash Rates Corresponding to Changes in Variables

Explanatory Variables	Change in Variable	Expected Percentage Changes in Crash Rates					
		Fatality	Fatal Crash	Injury	Injury Crash	PDO Crash	Total Crash
Speed-Related Variables							
Speed limit (10 mi/h change)	60-70	---	---	-3.82%	-4.31%	2.51%	1.23%
Speed limit (5 mi/h change)	65-70	---	---	-1.09%	-1.36%	2.69%	1.71%
Indicator for differential auto-truck speed limits	Yes	---	---	---	---	-6.20%	-3.79%
Roadway Design Variables							
Segment length (mile)	0.1	---	---	-4.93%	-5.20%	-5.47%	-5.19%
Horizontal curve length (ft)	100	---	---	-0.72%	-0.76%	-0.58%	-0.61%
Degree of curvature (°/100ft)	1	9.56%	9.53%	4.49%	4.43%	3.01%	4.22%
Vertical curve length (ft)	100	---	---	-0.69%	-0.69%	-0.57%	-0.66%
Vertical grade (%)	1	---	---	-5.96%	-9.71%	-10.62%	-9.81%
Indicator for median existence	1	---	---	2.02%	1.83%	2.70%	2.33%
Shoulder width (ft)	5	---	---	-26.91%	-28.14%	-28.60%	-28.29%
Number of lanes	1	-23.14%	-23.04%	---	---	6.86%	4.56%
Roadway Classification & Location Variables							
Indicator for interstate highway	Yes	---	---	---	-9.68%	-9.65%	-7.40%
Indicator for limited access	Yes	---	---	-12.90%	-14.52%	-6.49%	-9.30%
Indicator for principal arterial	Yes	---	---	9.05%	15.34%	---	7.64%
Indicator for rolling terrain	Yes	---	---	---	---	6.24%	---
Indicator for mountainous terrain	Yes	---	---	27.44%	24.74%	47.25%	27.83%
Indicator for rural area	Yes	---	---	---	---	-17.15%	-9.60%
Indicator for population < 50k	Yes	-30.88%	-30.13%	-9.58%	-9.02%	-8.16%	-9.20%
Indicator for northwest region	Yes	-28.82%	-28.15%	-18.12%	-16.38%	---	-7.72%
Indicator for northeast region	Yes	---	---	-16.40%	-18.17%	-7.37%	-11.68%
Indicator for southwest region	Yes	---	---	-23.04%	-24.68%	-3.89%	-12.17%
Indicator for southeast region	Yes	---	---	-11.95%	-13.81%	9.44%	---
Traffic Volume & Yearly Indicator Variables							
AADT per lane (veh/day/lane)	500	-3.36%	-3.40%	-0.64%	-0.59%	-0.74%	-0.82%
Indicator for year 2002	Yes	---	---	---	---	17.65%	11.37%
Indicator for year 2001	Yes	---	---	---	---	10.60%	8.28%
Indicator for year 2000	Yes	---	---	5.75%	5.46%	13.53%	11.51%
Indicator for year 1999	Yes	---	---	7.05%	7.90%	10.23%	10.77%
Indicator for year 1996	Yes	---	---	13.18%	11.31%	11.39%	13.55%
Indicator for year 1995	Yes	---	---	6.88%	4.65%	---	4.64%
Indicator for year 1994	Yes	---	---	3.11%	---	---	3.05%

Note: Rate percentage changes are based on the incident rate ratio (IRR).

Table F-4 – Difference Between Actual and Predicted Value

	Total Crash Count			Average Crash Rate (per Million VMT)		
	Actual Value	Model Prediction	Difference	Actual Value	Model Prediction	Difference
Fatalities	1289	1289	0.03%	0.024	0.023	-5.38%
Fatal Crash	1129	1130	0.05%	0.021	0.020	-5.25%
Injuries	72450	72442	-0.01%	0.926	0.949	2.52%
Injury Crash	45587	45669	0.18%	0.581	0.578	-0.52%
PDO Crash	57983	57804	-0.31%	0.724	0.732	1.10%
Total Crash	104699	103240	-1.39%	1.326	1.325	-0.02%

G Simple Crash Rate Change Model Using HSIS Data

The project's principal analyses of the effects of speed limit changes on crash counts and rates are described in Section 4.3 and, as explained there, were based on the creation and analysis of a panel dataset of clustered segment crash records from the Washington State HSIS.

The project also carried out a much more simplistic exploratory analysis of speed limit change effects using the original (unclustered) Washington State HSIS data. Although for a variety of reasons the results of this analysis were not statistically significant, it was felt that they were nonetheless interesting and suggestive enough to warrant presentation in this Appendix.

G.1 Data Preparation

The data used for the simplistic crash rate change analysis is the Washington State HSIS data for 1996, since that is the year when most speed limit changes occurred. In the 1996 dataset there are 62,237 high-speed homogeneous roadway segments (speed limits of 50 mi/h or more). As shown in Table G-1, the speed limit increased by 5 mi/h or more on 29,647 of these segments.

Each segment's crash rate was computed as the ratio of crash count to vehicle miles traveled (VMT), where VMT was estimated as the product of the segment's estimated AADT, length (as given in the HSIS dataset) and days of the speed limit being effective (either from January 1 to the date of the change, or from the date of the change to December 31). For segments that did not experience a speed limit change, the before and after crash rates were estimated for January 1 through March 15 and March 16 through December 31, since the NMSL repeal was officially implemented in March in Washington State.

For each of the five speed-limit-change categories (i.e., 0 mi/h, 5 mi/h, 10 mi/h, 15 mi/h and 20 mi/h), a VMT-weighted average of crash-rate changes was computed, as shown in Table G-2.

G.2 Model Estimation and Analysis

To see if the overall change[45] in crash rates rises or falls with speed limit changes, these data were used to estimate a simple weighted least squares (WLS) model involving only a constant, the speed change and its square. Each section's VMT was used as its weight since the variance of crash rates varies inversely with VMT, a consequence of the fact that VMT is the denominator in the crash rate calculation. Regression results are shown in Table G-3.

Based on this simple regression model, one may conclude the following:

- Ignoring all other factors (including variables like roadway design, traffic intensity [vehicles per lane mile], and vehicle type), the total crash rate is estimated to rise with an increase in

[45] *Changes* in crash rates, rather than overall crash rates, are analyzed here. This helps avoid any correlation between the error terms and speed limits, which would lead to biased estimates in models of total crash counts as a function of speed limits and other variables.

speed limit. For example, the total crash rate is estimated to rise by 0.40 crashes per million VMT following a 10 mi/h speed limit increase. Relative to the average total crash rate of 1.01 crashes per million VMT along high-speed roadways in Washington State in 1996, this effect is both statistically and practically significant.

- Further research reveals that the increase in total crash rate mainly comes from the PDO crash rate. For all other crash rates, the effect of speed limit is statistically insignificant.
- These results suggest that speed limit increases resulting from the 1995 NMSL repeal may have led to some increase in PDO crash rates on high speed roads in Washington, but that they had statistically insignificant impacts on more severe crash types.

Since this analysis ignores other factors that can affect crash rates, such as geometric roadway design and driver behavior, it is clearly quite superficial. On the other hand, the analysis admits a ready interpretation, and provides a confirmation of basic results obtained through a more rigorous approach.

Nonetheless, the limitations of the method and data must be noted. One data limitation is that the VMT estimates come from estimates of AADT, which are derived from a network sample, typically for only a few days during the year. Moreover, the dependent variable is obtained by dividing discrete crash count levels by a continuous variable (VMT), which does not make the resulting values truly continuous. Another issue is the practically zero goodness of fit statistics for all models, as shown in Table G-3. Had the segments been longer and/or experienced a greater number of crashes, the scatter in the data would likely have been less, and more interesting results might have emerged. Since crashes are such rare events, on short segments a one-year period is too brief for the modeling of crash rates as continuous values. This data limitation results in the many zeros in the dependent variable and hence the low R2.

The cluster analysis described in Section 4.3.1 was developed to circumvent this issue, by creating homogeneous clusters of segments and thus effectively lengthening the data.

Table G-1 – Count of Data Points by Speed Limit Change

SL Change (mi/h)	#Data Pt. Pairs
0	32,590
+5	24,076
+10	3,991
+15	1,544
+20	36
Total	62,237

Table G-2 – VMT-Weighted Average Crash Rate Changes by Category

SL Change (mi/h)	VMT-Weighted Average Total Crash Rate Change (Per Million VMT)	VMT-Weighted Average Injury Crash Rate Change (Per Million VMT)	VMT-Weighted Average Fatal Crash Rate Change (Per Million VMT)	VMT-Weighted Average Injury Rate Change (Per Million VMT)	VMT-Weighted Average Fatality Rate Change (Per Million VMT)	Total Site VMT in 1996 (in Millions)
0	0.163	0.103	0.005	0.235	0.005	4816.36
+5	0.274	0.138	0.004	0.238	0.005	16629.54
+10	1.003	0.367	0.002	0.818	-0.011	492.07
+15	0.289	0.102	0.004	0.264	0.009	690.75
+20	1.298	0.571	0.000	1.228	0.000	21.46

Table G-3 – Linear Regression Model of Average Crash Rate Change

Coefficient estimates and t-statistics										
Explanatory. Variables	Change in Crash Rate		Change of Injury Crash Rate		Change of Fatal Crash Rate		Change of Injury Rate		Change of Fatality Rate	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Constant	1.46E-01	2.77	9.76E-02	2.88	4.72E-03	0.78	2.21E-01	3.23	5.80E-03	0.78
Speed Limit Change	3.20E-02	1.91	1.09E-02	1.01	-1.32E-04	-0.07	2.18E-03	0.10	-1.96E-04	-0.08
Speed Limit Change Squared	-6.53E-04	-0.53	-3.83E-04	-0.48	2.07E-06	0.01	7.57E-04	0.47	8.57E-06	0.05
Goodness of Fit and Sample Size										
Adj. R-sqrd.	0.000		0.000		0.000		0.000		0.000	
Nobs.	62,237		62, 237		62, 237		62, 237		62, 237	